

HYBRID FSO/RF NETWORKS WITH NEURAL PREDICTION OF RSSI AND WEATHER

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ABSTRACT

This paper investigates neural network models for predicting weather parameters and received signal strength indicator (RSSI) to enable adaptive handover in hybrid free space optics (FSO)/radio frequency (RF) systems. The most correlated parameters were visibility, temperature (measured from three independent sensors), and particle concentration. The work was exclusively focused on predicting correlated atmospheric effects and subsequently predicting RSSI parameter derived from them using a long short-term memory (LSTM) model, minute by minute over 24 hours. The predicted values can in the future serve as input for initiating handover decisions – for example, through visualization in Simulink. The threshold value of -30 dBm was taken from peer-reviewed articles and is used as a reference limit for link quality.

Keywords: Switching of hybrid FSO/RF systems, LSTM, RSSI, RNN, prediction.

1. INTRODUCTION

Hybrid FSO/RF systems represent a revolutionary leap in wireless communication technology, seamlessly integrating the advantages of two distinct transmission methods, namely free-space optics and radio frequency. This cutting-edge combination increases the efficient use of available resources while reducing the inherent limitations associated with each technology. In our current digital era, where the demand for connectivity and data transfer is at an unprecedented level, the need for reliable and fast communication solutions is increasingly important. This need applies to a wide range of sectors, including commercial telecommunications networks and critical infrastructure, such as healthcare facilities and industrial processes, where reliable communication systems are not only advantageous but also essential for successful operation.

Hybrid FSO/RF systems, however, also bring their own limitations. One of the main obstacles these systems face is their vulnerability to atmospheric conditions. Elements such as poor visibility, atmospheric turbulence due to temperature fluctuations, high particle concentration and other environmental factors in which such a hybrid system is deployed can significantly affect the quality and reliability of signal transmission. This sensitivity can lead to performance deviations that can compromise the efficiency of communication systems. Given these limitations, hybrid FSO/RF systems represent a promising alternative that offers potential solutions to some of the difficulties caused by adverse weather conditions. The use of hybrid systems allows for dynamic adaptation of the transmission path to current conditions. Depending on the implementation, the system can operate in two ways, namely hard channel switching or soft channel switching. In hard switching, the connection is strictly switched between the FSO and RF channels based on a certain signal threshold, while in soft switching, the data flow is smoothly divided between both channels, which ensures more stable and efficient communication. [1].

In this paper, we will explore the role of neural networks in optimizing hard link switching within these hybrid systems. The aim of our research is to investigate the significant impact that neural networks can have on weather forecasting and, from this forecast, to predict the RSSI parameter. Both of these factors are essential for the effective management of transitions between optical and radio links, ensuring that communications remain stable and reliable under varying conditions. In this paper, we exclusively focus on predicting the atmospheric effects that show the highest correlation with the RSSI parameter, and subsequently implement the prediction of the RSSI itself. We analyze the performance of the proposed neural network model and compare it with traditional approaches to identify its advantages and limitations in the context of hybrid FSO/RF systems.

Through this research, we aim to provide a thorough understanding of how neural networks can be applied in this specific context, and to clarify their potential benefits as well as the challenges they may pose in future work. Our goal is to improve the understanding of these technologies in the field of wireless communication and to support their further development and integration into an increasingly connected digital environment. By achieving this goal, we aim to lay the foundation for more robust and efficient communication systems that can adapt to the evolving demands of modern society. The rest of this paper is organized as follows: Section 2 presents the theoretical background and related work. Section 3 describes the methods and design of the LSTM model. Section 4 discusses the results, and Section 5 concludes the paper and outlines future work.

2. SUBJECT

In this chapter, a comprehensive survey of the application of neural networks, specifically LSTM, in hard switching optimization within hybrid FSO/RF systems is presented. The primary focus is on the prediction and updating of atmospheric influences that significantly affect the RSSI parameter, which is crucial for effective

communication in these systems.

The paper begins by outlining the challenges posed by atmospheric conditions in wireless communications. To address these challenges, the paper presents an LSTM neural network as a robust solution capable of learning long-term dependencies in sequential data, thereby increasing the accuracy of atmospheric impact prediction.

2.1. Hybrid FSO/RF systems

Hybrid FSO/RF systems are a modern communication solution that combines the advantages of two technologies, optical transmission in free space and radio transmission. The goal of this combination is to overcome the disadvantages of individual transmission methods and ensure reliable data transmission even in difficult conditions. The main advantage of hybrid systems is high availability and reliability. The system can automatically switch between FSO and RF transmission according to current conditions. For example, in case of poor visibility (fog, rain), the system switches from FSO to RF, thus ensuring uninterrupted communication.

Hybrid systems also offer high transfer rates thanks to FSO, which is ideal for data-intensive applications (e.g. video transmissions). If conditions are unfavorable, they switch to RF, which has lower latency. In addition, FSO provides greater security because laser beams are difficult to intercept, and when combined with RF, data can also be encrypted.

The disadvantage of these systems is the complexity of their implementation and maintenance, which increases costs. They are also affected by external factors. FSO can be affected by weather, while RF suffers from interference and signal attenuation.

Overall, hybrid FSO/RF systems are a promising solution for reliable and secure communications, but their deployment requires careful consideration due to complex implementation and operational costs [2]. Fig. 1 shows the components required for a hybrid FSO/RF system.

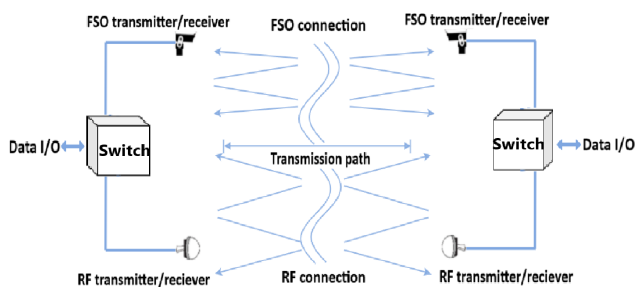


Fig. 1 Components for a hybrid FSO/RF system

In hybrid FSO/RF systems, we can distinguish two types of switching mechanisms, hard and soft switching. Hard switching in hybrid FSO/RF transmission systems is a mechanism that allows dynamic transitions between two different transmission channels depending on the current transmission conditions. An important aspect of hard switching is that only one of the two transmission

channels is active at a given time, which reduces power requirements and simplifies the design of the receiver, which does not have to combine signals from both channels. This system is designed to optimize communication performance and reliability, with the FSO link being preferred when conditions are favorable. The FSO link, which uses optical signals to transmit data, tends to provide higher transmission rates and capacities, but is sensitive to atmospheric conditions such as fog, rain, or turbulence, which can cause signal degradation [3], [4]. The RSSI parameter is often used to make a switch decision, with expert studies indicating a reference value of -10 dBm to -30 dBm at which the switch from FSO to RF channel is initiated [5]. The Fig. 2 demonstrates the hard switching of the hybrid FSO /RF system.

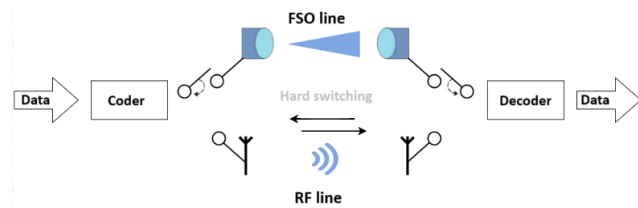


Fig. 2 Hard switching hybrid FSO/RF system

In contrast, soft switching in hybrid FSO/RF systems is a mechanism where both channels are active simultaneously and dynamically share the load according to the current signal quality. The result is a smooth adaptation of the transmission without dropouts, which increases the overall stability and reliability of the system. In soft switching, both channels transmit data continuously, with the main channel, typically the FSO, carrying most of the data load, and the auxiliary RF channel serving as a backup when conditions on the optical channel deteriorate. This scheme works by monitoring the signal quality in real time and dynamically deciding, based on the RSSI value, what proportion of data will be transmitted over the FSO and what over the RF.

If the quality of the optical signal decreases due to atmospheric conditions (e.g. fog), a larger proportion of data is moved to the RF channel, minimizing the risk of transmission dropouts. When conditions improve, the system smoothly returns to the priority use of the FSO channel [6]. The Fig. 3 demonstrates the soft switching of the hybrid FSO/RF system.

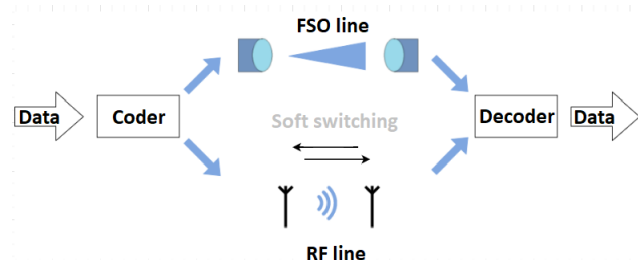


Fig. 3 Soft switching hybrid FSO/RF system

2.2. Optimization of input data

In our study, we focused on analyzing the relationships between the RSSI parameter and various atmospheric factors such as temperature, pressure, humidity, wind speed, particle concentration and visibility. For this purpose, a correlation analysis was performed to determine the relationships between these variables.

Pearson's correlation coefficient (r) was used to evaluate these relationships. This coefficient is a widely used tool in statistics that measures the linear relationship between two variables. Its value ranges from -1 to $+1$, while:

- **Complete positive linear relationship:** A value of $+1$ indicates a perfect positive correlation, meaning that if one variable increases, the other increases in the same proportion.
- **Complete negative linear relationship:** A value of -1 indicates a perfect negative correlation, meaning that as one variable increases, the other decreases.
- **No linear relationship:** A value of 0 means that there is no linear relationship between the variables.

Pearson's correlation coefficient is calculated using a formula (1) that takes into account the deviations of individual values from their averages [7].

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \quad (1)$$

where x_i and y_i are the individual values of the variables, $\bar{x}$ and $\bar{y}$ are their means, and $\sum$ denotes summation. The numerator of the formula represents the covariance between the variables, while the denominator normalizes it using standard deviations. This formula quantifies the strength and direction of the linear relationship between two variables, in this case, the linear dependence between the RSSI parameter and the other variables such as temperature, humidity, particle concentration, etc.

This coefficient makes it possible to quantify the strength and direction of the relationship between RSSI and other variables, which is crucial for optimizing communication prediction and control in hybrid FSO/RF systems.

After conducting various experiments, we found that Pearson's correlation coefficient provides accurate and useful information about the relationships between parameters, which helped us better understand how atmospheric factors affect signal quality and overall system performance.

Table 1 shows the results of calculating the Pearson correlation coefficient between parameters X and Y . Parameter X represents the RSSI values, while parameters Y include individual atmospheric phenomena such as temperature, pressure, humidity, wind speed, particle concentration and visibility. The values temperature1, temperature2, and temperature3 came from three independent sensors placed at different locations to eliminate local environmental influences, and were then averaged to reduce unnecessary duplicate calculations. Similarly, wind speed1 and wind speed2 were obtained from two separate, mutually independent sensors and then

averaged. The results shown in the Table 1 were obtained by calculating the correlation between RSSI and each of these atmospheric parameters. The calculations were performed in the PyCharm environment using the Python language and the *scipy.stats.pearsonr*(x,y) method. The Fig. 4 shows a fragment of the database from which these values were taken.

Table 1 Results of the correlation coefficient between RSSI and individual atmospheric influences

X Value	Y Value	Pearson correlation coefficient (r)
RSSI	RSSI	1.000
RSSI	Temperature1	0.145
RSSI	Pressure	0.053
RSSI	Temperature2	0.130
RSSI	Humidity	-0.007
RSSI	Temperature3	0.167
RSSI	Windspeed1	-0.010
RSSI	Windspeed2	-0.010
RSSI	Particleconcentration	0.177
RSSI	Visibility	0.264

The input data were converted from an .xlsx table to a .csv file for use in development environments.

13.10.2023;8:55;-26;14.4;994.715;12.95;
79.6500015;10.437;0.3940265;0.3965745;11;4000

13.10.2023;8:56;-26;13.9;994.63;12.9;
77.950001;10.437;0.7807575;0.409075;14;4000

13.10.2023;8:57;-26;13.9;994.685;12.9;
79.75;10.437;0.780757;0.409075;13.5;4000

Fig. 4 A sample of the dataset intended for neural network learning

The dataset includes date, time, RSSI signal strength, three temperature values, pressure, humidity, two wind speed measurements, particulate matter concentration, and visibility, each recorded in their respective units. The sample .csv file in the Fig. 4 shows data from 13.10.2023 in the time period interval from 8:55 to 8:57. Individual data in the .csv file are separated by semicolons, which divides them into individual columns. These data, which were obtained from the weather station Technical University in Košice, which represent part of the entire database, the whole database contains 85 125 records.

3. METHODS

This chapter deals with the design and implementation of algorithms for predicting and updating the atmospheric

effects that most affect the RSSI parameter, and as calculated by the *Pearson* correlation coefficient, these effects are temperature, particle concentration, and visibility. These three atmospheric effects have the largest positive correlation with the RSSI parameter. These effects were included in the prediction models to speed up and simplify the computational complexity, since the other effects did not have a significant impact on the RSSI parameter. All three atmospheric effects were predicted using an LSTM network. LSTM is a type of recurrent neural network (RNN) architecture. It is specifically designed to solve the vanishing gradient problem that often occurs in traditional RNNs. This allows LSTM networks to efficiently learn and preserve long-term dependencies in sequential data, making them particularly suitable for tasks involving time series analysis and prediction.

In this paper, a neural network model is created using the LSTM algorithm to predict atmospheric data based on the latest known data. The model is designed to effectively capture the dynamics of time series and predict future values of individual atmospheric effects.

The predicted values of atmospheric effects were subsequently used as input data for another LSTM neural network model, the goal of which was to predict the RSSI parameter itself based on the expected development of conditions that have the most significant impact on

its value. The LSTM algorithm is chosen for its ability to preserve long-term relationships between data and remember information from previous time periods, which is important for successful RSSI parameter prediction [8] [9]. The cell architecture of the LSTM network can be seen in the Fig. 5.

These neural network models are designed to work efficiently with time series and overcome memory decay, a common problem with traditional RNNs. The results of these models should provide better performances in time series prediction and sequence analysis compared to other approaches [10].

The LSTM neural network was chosen for this study because it can effectively capture long-term dependencies in sequential data, which is crucial for predicting time series such as atmospheric effects and RSSI. The Gated Recurrent Unit (GRU) and Convolutional Neural Network – Long Short-Term Memory (CNN-LSTM) architectures were also considered as alternatives. GRU is a simplified and computationally less demanding version of LSTM, while CNN-LSTM combines convolutional and recurrent layers and allows capturing both spatial and temporal patterns in the data. Despite these capabilities, LSTM was preferred due to its high accuracy in predicting long-term dependencies in environmental data.

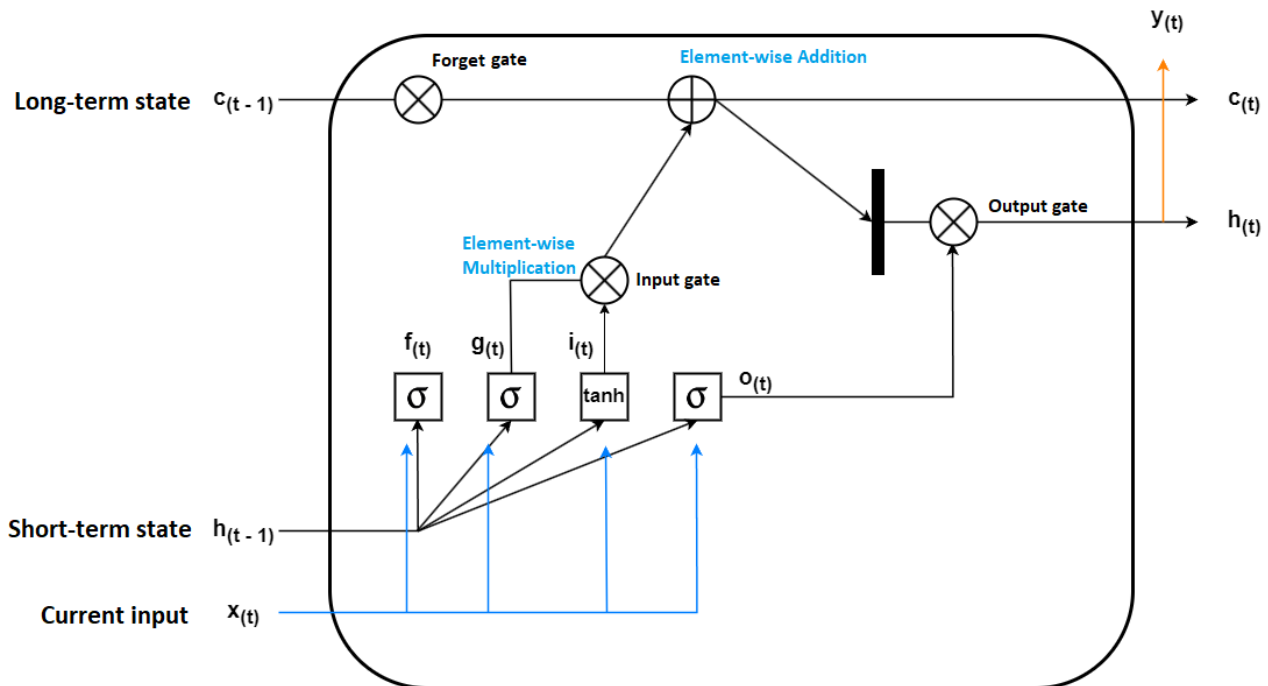


Fig. 5 LSTM cell architecture

3.1. Design of neural network models for weather prediction and RSSI parameter

In this study, we designed and implemented two neural network models using the LSTM algorithm for weather forecasting and RSSI parameter in hybrid FSO/RF

systems. The first three models were focused on predicting atmospheric effects, namely temperature, visibility and particle concentration. First, we preprocessed the dataset and identified the main factors with high correlation with the RSSI parameter. This preprocessing step was crucial because it ensured that the model was trained on the most

relevant features, thus improving its prediction capabilities. The relationship between these three parameters and the RSSI parameter is based on the positive correlation between the RSSI parameter and the given parameters. We can also see this in Fig. 4, specifically on the first line at 8:55, where a fragment of the used data set is shown. The RSSI parameter values are very good -26 dBm, because the visibility is very good at 4000 m, the particle concentration is also low at 11 $\mu\text{g}/\text{m}^3$, and the temperature is on average 14.4 °C.

We then built an LSTM model that predicted these factors 24 hours ahead, minute by minute. This temporal granularity is particularly important for applications requiring real-time data, as it allows for timely adjustments to communication strategies. We first split the data into training and testing sets to ensure that the model could be evaluated on unseen data and to assess its generalization capabilities. To further improve the model's performance, we modified the input data to create training datasets, including techniques such as normalization and data augmentation. We implemented a model with two LSTM layers and one subtraction layer, optimized using the Adam algorithm and a mean square error loss function.

The inclusion of dropout layers was necessary to prevent overfitting, which can occur when models are too complex compared to the amount of training data available. Finally, we evaluated the model using metrics such as the mean square error. This metric provided a comprehensive view of the model's performance, allowing us to quantify its accuracy and reliability in predicting atmospheric conditions and RSSI values.

4. RESULTS AND DISCUSSION

As mentioned in subsection 2.2, the values of the RSSI parameter are most influenced by atmospheric influences, such as temperature, particle concentration and visibility, which can also be seen in Table 1. Their values were predicted by the LSTM algorithm. The data were manually divided into training data in the interval from 12.10.2023 to 6.12.2023 and test data in the interval from 7.12.2023 to 7.12.2023. Subsequently, predictions were made in standard ratios of 90:10, 80:20 and 70:30. The data were trained from every minute. Tables 2 to 5 show the results of the prediction of atmospheric influences. Individual Tables 2 to 6 show the time needed to train the data, the mean square error MSE and the percentage prediction accuracy of individual models. The success of the individual models can be seen from figures Fig. 6 to Fig. 9.

Table 2 The table shows the results of the prediction of atmospheric impacts, divided by data manually

Atmospheric impacts	LSTM Model Training Time	MSE	Percentage Accuracy
Temperature	1413.69 seconds	0.24366	77.57%
Particle concentration	1413.98 seconds	0.49977	81.60%
Visibility	1418.28 seconds	0.68259	99.65%

Table 3 The table shows the results of the prediction of atmospheric influences, divided by the data in the ratio of 90:10

Atmospheric impacts	LSTM Model Training Time	MSE	Percentage Accuracy
Temperature	1297.77 seconds	0.01856	99.38 %
Particle concentration	1291.39 seconds	1.14805	57.64%
Visibility	1277.99 seconds	0.70102	99.86%

Table 4 The table shows the results of the prediction of atmospheric influences, divided by the data in the ratio of 80:20

Atmospheric impacts	LSTM Model Training Time	MSE	Percentage Accuracy
Temperature	1236.66 seconds	0.10786	95.90%
Particle concentration	1240.19 seconds	1.07243	57.57%
Visibility	1236.79 seconds	0.68209	99.86%

Table 5 The table shows the results of the prediction of atmospheric influences, divided by the data in the ratio of 70:30

Atmospheric impacts	LSTM Model Training Time	MSE	Percentage Accuracy
Temperature	1142.74 seconds	0.24147	89.10%
Particle concentration	1136.53 seconds	0.79461	59.58%
Visibility	1144.09 seconds	0.54686	99.86%

The figures Fig. 6, Fig. 7, Fig. 8 are showing 24-hour prediction of atmospheric influences in the order of temperature, visibility and particle concentration, with a training-to-testing data ratio of 70:30.

Table 6 The table illustrates the result of RSSI parameter prediction

RSSI Data Split	Model Training Time	MSE	Percentage Accuracy
Manual data split	116.085896 seconds	1.29583	96.39%
90:10	117.037107 seconds	1.27643	96.39%
80:20	94.418121 seconds	1.27628	96.39%
70:30	91.305367 seconds	1.47492	96.60%

The Table 6 demonstrates the results of predicting the RSSI parameter using the LSTM algorithm, where the data were manually divided into training data from 12.10.2023 to 6.12.2023, and testing data on 7.12.2023. Predictions were further conducted using standard ratios: 90:10, 80:20, and 70:30. Data were trained at each minute. Based on the provided Tables 2, 3, 4, 5, it is possible to deduce that the best predictions in terms of MSE and overall prediction success are shown for temperature, as the temperature values did not change drastically over time. On the contrary, the worst prediction results are exhibited for particle concentration, even though the MSE error is relatively small, the prediction accuracy is not very precise, as the values of particle concentration changed radically in small time intervals.

Just as with the prediction of atmospheric influences, the prediction of the RSSI parameter itself showed that the best results were achieved with a training-to-testing data ratio of 70:30. The Fig. 9 illustrates a graphical visualization of the prediction success of the RSSI parameter.

5. CONCLUSION

This article presents the application of a recurrent neural network of the LSTM type in hybrid FSO/RF communication systems, with the aim of predicting critical states that require switching between optical and radio transmission channels. The proposed approach involves a two-step prediction. In the first step, selected atmospheric influences (temperature, visibility, particle concentration) that have a fundamental impact on the propagation of the optical signal are predicted using the LSTM network. In the second step, the RSSI parameter is predicted based on these predicted values.

As can be seen from the provided graphs in Figures 6 to 9 and Tables 2 to 6, the prediction results achieved a success rate higher than 90%, with a data split in the ratio of 70:30, which from a scientific point of view confirms that the proposed model can reliably identify upcoming degradations of transmission conditions and support the decision-making process about switching the line. The prediction of particle concentration turned out to be somewhat worse, since it changes very quickly in a short time interval. The resulting system thus contributes to increasing the reliability of the hybrid connection and minimizing communication failures.

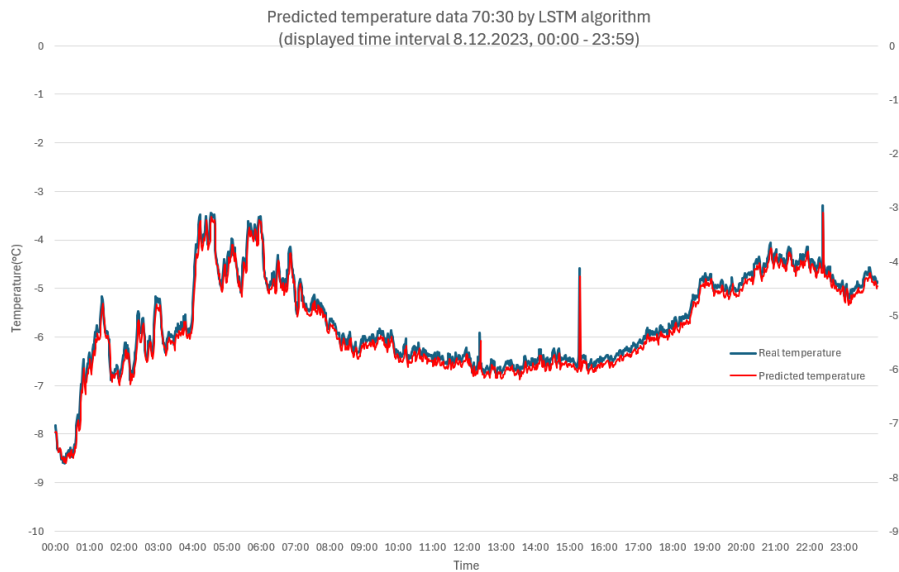


Fig. 6 Graph showing the results of temperature prediction in the ratio of training and testing give 70:30

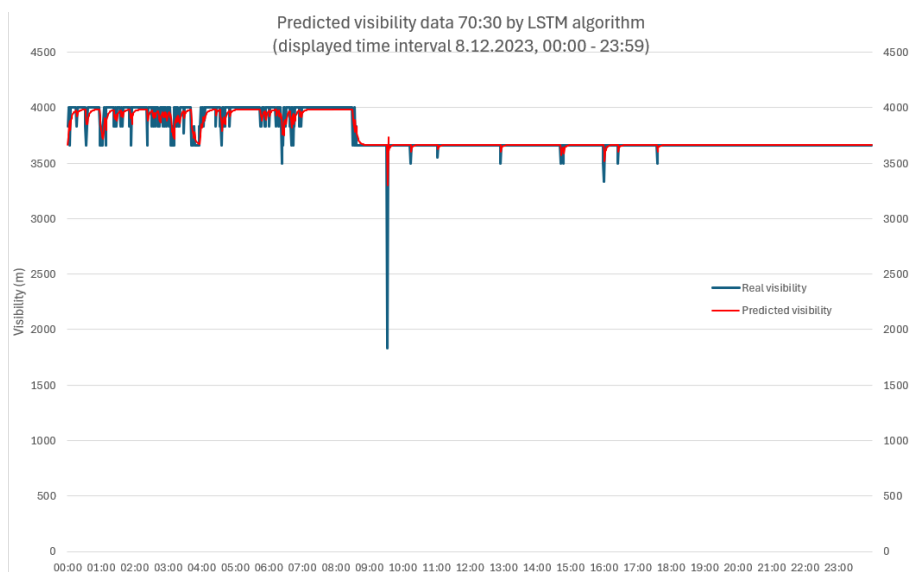


Fig. 7 Graph showing visibility prediction results in the ratio of training and testing give 70:30

The use of LSTM networks for switching links in hybrid FSO/RF systems represents a significant step towards

intelligent control of wireless communication. The model allows for early predictions with respect to the dynamics

of the atmospheric channel, thus ensuring a smooth and adaptive transition between FSO and RF transmission in the future.

Future research should focus on the design of efficient neural network architectures specifically tailored to hybrid FSO/RF systems, with an emphasis on low computational complexity and the ability to work in real time. The key challenge also remains the optimization of data

preprocessing and their reliable scaling in long-term and large-scale scenarios. In particular, appropriate scaling could improve the prediction of particle concentration in the air in the future.

The results of this work indicate that LSTM networks represent a promising tool for increasing prediction accuracy, reliability, and operational efficiency in the environment of hybrid FSO/RF communication systems.

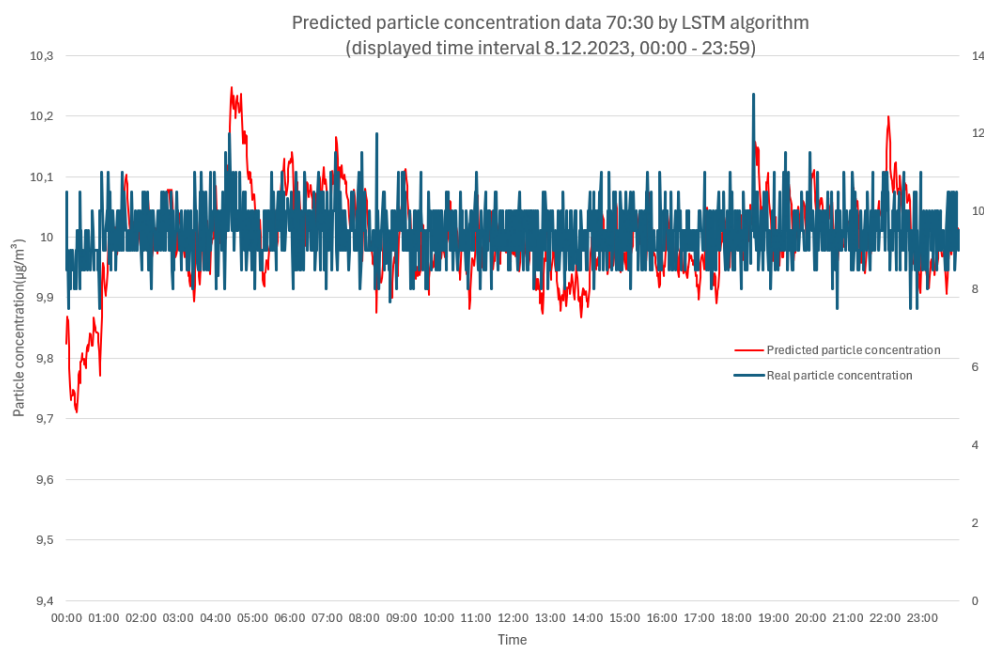


Fig. 8 Graph showing particles concentration prediction results in the ratio of training and testing give 70:30

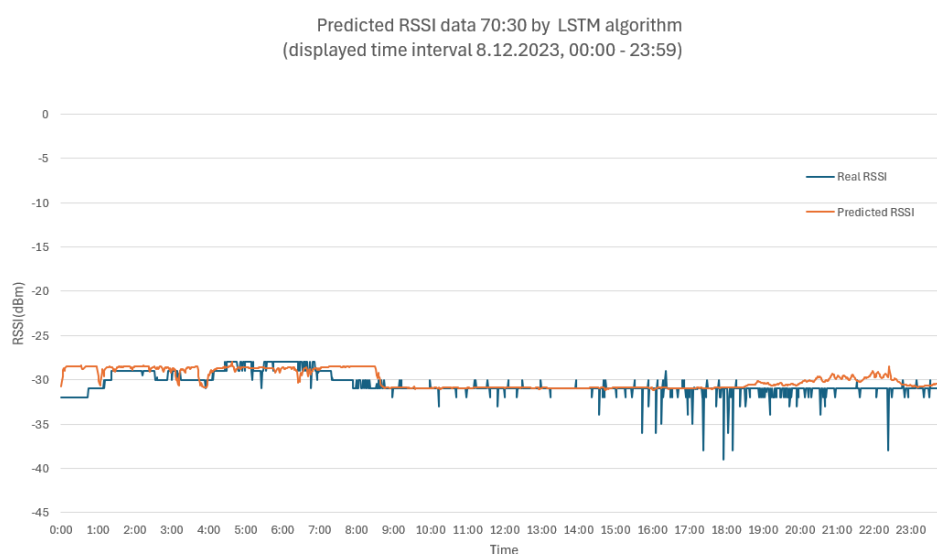


Fig. 9 Graph showing RSSI prediction results in the ratio of training and testing give 70:30

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