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Communication RSSI Prediction and Validation Framework for Advanced Air Mobility

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***Abstract*—This paper proposes a communication signal strength prediction and validation framework for the use of advanced air mobility. Advanced air mobility, including urban air mobility and unmanned aerial vehicles, requires a scalable, safe, and seamless communication infrastructure different from conventional aircraft. This paper proposes a hybrid regression-based prediction method that combines synthetic data generated from a ray-tracing model and real flight test data in the urban airspace and uses k-fold cross-validation to evaluate the predicted signal strength. The results show that the proposed framework provides reliable performance indices, effectively mitigating the insufficiency of flight data. This research will enable evaluating the communication infrastructure and identifying high-risk areas for advanced air mobility stakeholders.**

***Index Terms*—Advanced Air Mobility (AAM), hybrid regression, ray tracing, Received Signal Strength Indicator (RSSI)**

I. Introduction

Advanced Air Mobility (AAM), which includes urban air mobility with electric Vertical Take-Off and Landing (eVTOL) aircraft and Unmanned Aerial Systems (UAS), is emerging as a sustainable and efficient future transport. However, the potential of AAM can only be fully realised if the underpinning communication infrastructure is robust and reliable, ensuring seamless interaction between the vehicles and ground systems. Areas with insufficient quality of signals should be effectively avoided to de-risk the operations while minimising the detour. Substantial technological challenges lie in accurately predicting the communication signal performance in urban canyons with numerous sources of signal interference.

Prediction of the Received Signal Strength Indicator (RSSI) in general has been a widely investigated area. Ray-tracing model [1] is one of the most well-known communication models to simulate signal propagation paths, including reflections and diffractions, to predict path loss. As the ray-tracing model is computationally expensive, other alternatives have been suggested as dominant path model [2] and empirical models [3], which can be used for preliminary prediction of RSSI. These communication models have been a basis for many model-based data fitting methods with data, including tomography with low-rank structure [4], sparsity-based method [5], and piecewise homogeneity approaches [6], [7]. However, these works have been mostly focused on urban surface or indoor environments. To the best of the authors' knowledge, there has been no previous work that has predicted and validated the RSSI in the 3D urban airspace for the operation of UAS, where the validity of the model-based approaches remains largely unknown. Key reasons behind the lack of research in AAM-specific communication evaluation are suggested as difficulties in getting real flight data, as AAM is an emerging area, and safety and security of the operation of UAS are key remaining risks to overcome.

Data-driven approaches have also been investigated to predict RSSI in unknown model environments. The most commonly used methods are regression, but these have also been extended with combinations of support vector machine [8], kriging [9] to estimate RSSI based on spatial correlation, and tensor completion [10] to complete missing data in multi-dimensional arrays by decomposing data into low-rank tensors. While data-driven approaches are informative in unknown models, a key challenge lies in the lack of real flight test data in urban low-altitude airspace.

This research aims to provide high-fidelity 3D communication RSSI prediction and validation frameworks by effectively combining model-based and data-driven approaches. The communication prediction framework involves generating synthetic data from the ray-tracing model and combining them with the UAS flight data. The combination of synthetic data mitigates the insufficiency of flight test data and enables extrapolation to areas where tests are not conducted. The predicted RSSI is validated with the measured test data with respect to key performance indices of Root Mean Squared Error (RMSE) and accuracy. The validation framework is designed with k-fold cross-validation to also mitigate the lack of test data. The results show that the proposed combination of

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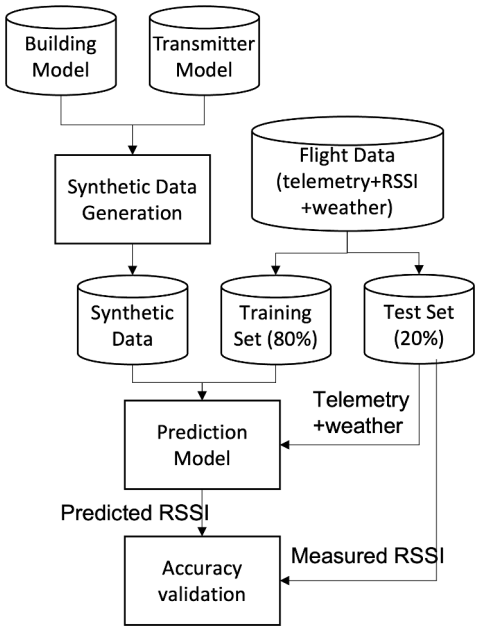


Fig. 1: Algorithm Flowchart

synthetic and real data improves the prediction performance, and the cross-validation ensures robustness and scalability of the framework. The proposed frameworks will allow the AAM stakeholders to identify the high-risk areas and plan the flight operations accordingly.

The rest of the paper is composed as follows: Sections II and III details the proposed prediction and validation frameworks for AAM. The results including the flight test settings are presented in Section IV. The conclusion and future works are proposed in Section V.

II. Prediction Framework

The overall flowchart is shown in Fig. 1. The prediction framework consists of synthetic data generation, and the prediction model combining the synthetic and real flight data. Based on the known building locations and dimensions, the radio propagation from the transmitter is simulated using the ray-tracing model. The simulated synthetic data is combined with 80% of the real test data, which contains telemetry, measured RSSI, and weather information. If the prediction model receives a flight plan, it produces the predicted RSSI along the trajectory based on the combined data. The rest (20%) of the real test data is used to validate the accuracy of the prediction model, by providing the telemetry and weather to the prediction model, and comparing the predicted RSSI with the measured values. The ratio of 80% and 20% has been chosen in accordance with the conventional composition of machine learning-based methods. Key functionalities – synthetic data generation, prediction model, and accuracy validation – are detailed in the rest of the section.

A. Synthetic Data Generation

1) Ray-Tracing Model: The ray-tracing model implemented as MATLAB toolboxes [11] is used as a foundation to generate synthetic communication datasets, which are instrumental in training and validating prediction models. The ray-tracing model provides a detailed representation of signal behaviour by calculating the path taken by signals in the presence of obstacles. It is especially useful for environments with multiple reflecting surfaces in urban areas. The drawback is that it is computationally intensive, making it unsuitable for real-time applications in large-scale environments. To mitigate the computational complexity, the synthetic data is generated once for the entire area and then attenuated with the effect of environmental factors. Furthermore, the accuracy of the ray-tracing model depends on the precision of the building model, which poses an upper bound on accuracy. Therefore, to address potential inaccuracies in building models, unknown environmental factors should be modelled via various scenarios or flight data.

2) Environmental Attenuation Model: Rain and humidity are known to attenuate RSSI. The effect of rain is modelled as [12]:

$$L = d_{eff} \cdot r \cdot k \cdot R^{\alpha} \tag{1}$$

where L is the synthetic RSSI, d_{eff} is the effective propagation distance, R is the rain rate, k and α are constants determined by the transmitter frequency f, and r is the scale factor for the effective propagation distance calculated as:

$$r = \frac{1}{0.477 d^{0.633} R_{0.01}^{0.73\alpha} f^{0.123} - 10.579(1 - \exp(-0.024 d))}. \tag{2}$$

where d is the propagation distance, $R_{0.01}$ is the rain rate exceeded 0.001% of the time.

The attenuation coefficient from humidity is modelled as [13]:

$$\gamma_c = K_l \cdot \rho_l \tag{3}$$

where ρ_l is the humidity, and K_l is the attenuation coefficient calculated as:

$$K_l = \frac{0.819 f}{\epsilon''(f)(1 + \eta(f)^2)} \tag{4}$$

where $\eta(f) = (2+\epsilon'(f))/(\epsilon''(f))$ and the $\epsilon(f)$ is the complex dielectic permittivity of water.

These attenuation models can be combined with the ray-tracing model to include the environmental variations to generate synthetic data and better predict in different weather conditions.

B. Synthetic and Flight Data Combination

The linear regression for the scattered 3D locations, rain rate and humidity is given by:

$$\hat{L}_t = \sum_{i=1}^{k} \beta_i x_{it} + \epsilon_t \tag{5}$$

where $\hat{L}_t$ is the predicted RSSI at time t, x_{it} is the i-th observation of the variables at time t, k is the number of observations, ϵ_t the error term, and β_i are parameters to be estimated. The linear model is fitted such that the error term $\epsilon = \hat{\mathbf{L}} - \mathbf{X}\beta$ is minimised.

Here, the observation data x_{it} is an augmentation of synthetic and real flight test data, such that

$$x_{it} = \begin{bmatrix} x_{1t}^{syn} & \cdots & x_{nt}^{syn} & x_{1t}^{real} & \cdots & x_{mt}^{real} \end{bmatrix}^T, \quad (6)$$

where n and m are the number of observations of synthetic data $\mathbf{X}^{syn}$ and real flight test data $\mathbf{X}^{real}$ at time step t, satisfying $k = n + m$. As the amount of flight test data accumulates, less weight is imposed on the synthetic data, making the predicted RSSI to be more dependent on the flight test data.

III. Validation Framework

A. Key Performance Indices

Two key performance indices are suggested as RMSE and accuracy. RMSE is defined as:

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{t_f} |\hat{L}_t - L_t|^2}{t_f}} \ (\text{dB}) \quad (7)$$

where t_f is the total number of time steps of each flight plan. RMSE provides an interpretable error value in the same units as the original data, making it easier to understand the practical magnitude of prediction errors.

To show how close the predicted RSSI values are to the measured values from the flight tests on average, the accuracy is calculates as:

$$\text{Accuracy} = \left(1 - \frac{\sqrt{\sum_{t=1}^{t_f} |\hat{L}_t - L_t|^2}}{\sum_{t=1}^{t_f} |L_t|}\right) \times 100 \ (\%). \quad (8)$$

The accuracy provides a relative measure of error, indicating how large the prediction error is relative to the variability in the ground truth. This helps assess how well the model performs independently of the signal strength variations, providing a standardised error metric across different maps or datasets.

B. k-Fold Cross-Validation

5-fold cross-validation as shown in Fig. 2 is implemented to improve the prediction and evaluation in regression with limited test dataset. By averaging results across multiple folds, it provides a more reliable estimate of the performance compared to a single train-test split. In each fold, synthetic and real flight data of the training set are combined to predict the RSSI of the testing set. Then, the mean RMSE and accuracy are calculated with respect to the measured RSSI of the testing set and averaged across the folds.

IV. Results

A. Flight Test Results

Flight tests have been conducted in Milton Keynes city centre, United Kingdom, across 3 different days. Parrot Anafi AI has been selected for drone capture flights, as it provides a simple SDK for RSSI measurement and flight data extraction. The drone used for the test and the flight test area are shown in Fig. 3. Two areas have been measured: **Area 1** departing from South Second Street Car Park (52.034 N, -0.767 E) and

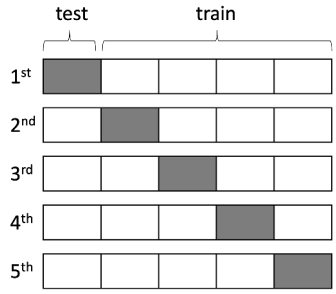
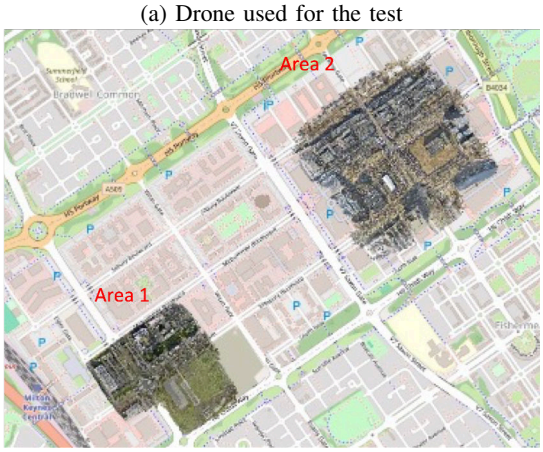


Fig. 2: 5-Fold Cross-Validation

(a) Drone used for the test

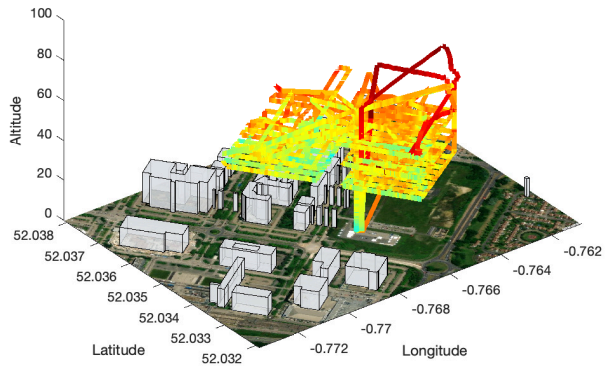


(b) Flight test area

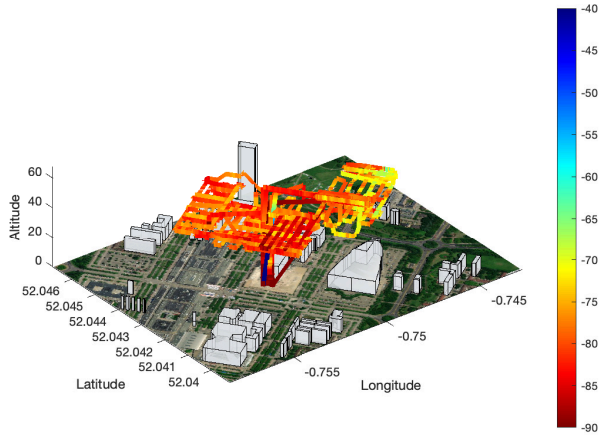
Fig. 3: Flight experiment setup

Area 2 departing from an old food court (52.043 N, -0.752 E). 8 flight tests were conducted in Area 1, and 4 tests in Area 2. The flight trajectory is designed at fixed altitudes of 30, 40, and 50m with the size of x-y grid 5 m. The data has been recorded in 10Hz frequency. The flight tests have been conducted in different environmental factors with 2-11 degree Celsius and 60-98% humidity.

The measured RSSI is visualised along the flight trajectory in Fig. 4. The mean RSSI is -74.2 and -80.2 dBm, and the standard deviation is 4.9 and 7.6 dBm for Area 1 and 2, respectively. It is shown that the signal strength is in general

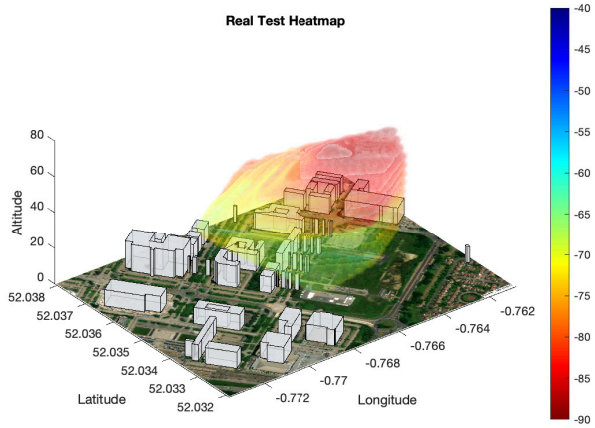


(a) Area 1

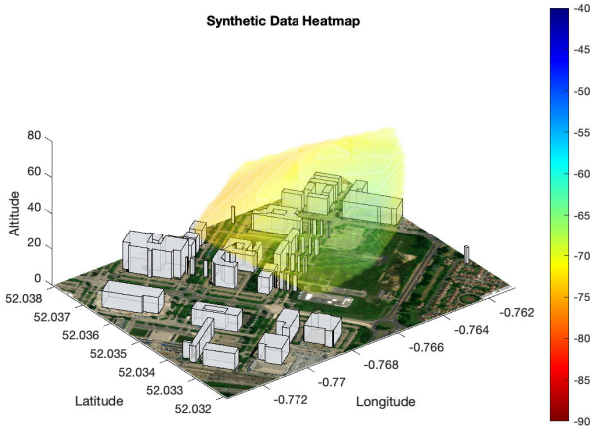


(b) Area 2

Fig. 4: Flight trajectory with measured RSSI



(a) Real test data



(b) Synthetic data

Fig. 5: Synthetic data comparison in Area 1

poor for the current AAM to operate without any additional communication device, and has high standard deviation with outliers and interference.

B. Synthetic Data Generation Results

The building structures of OpenStreetMap and MATLAB communication toolbox has been used to generate the synthetic data, based on the known locations of the towers (52.040 N, -0.761 E) and (52.030 N, -0.766 E).

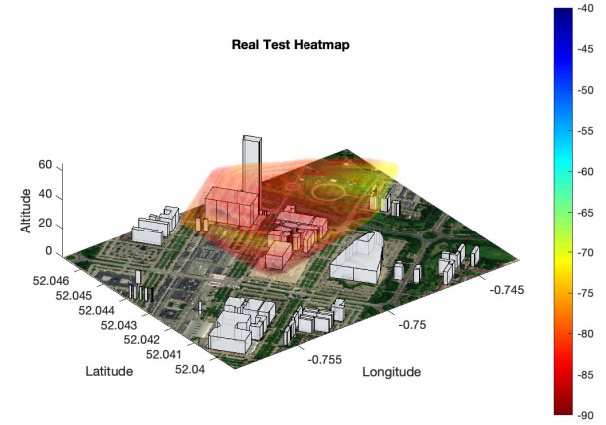
The synthetic data generated for Area 1 and 2 are compared with the real test data regressed for the heatmap visualisation in Figs. 5 and 6. High-risk areas are shown in red colour such that the AAM stakeholders can effectively derisk their flight plans. The mean RSSI of the synthetic data is -71.3 and -75.7 dBm, and the standard deviation is 1.9 and 1.7 dB for Area 1 and 2, respectively. Directly comparing with the real test data, RMSE is calculated as 6.0665 and 9.4527 dB for each area, with the accuracy of 91.8 and 88.2 %. These values may be acceptable for outdoor experiments considering that indoor communication modelling offers 95% accuracy [14] and outdoor environment contains much greater uncertainties in humidity, interference, and sensor noise. However, from the perspectives of AAM, 90% of communication model accuracy imposes risk in communication loss or degradation and operation inefficiency in conservatively avoiding the risky areas. The ray-tracing model alone cannot provide sufficient safety or efficiency for AAM usage, hence requiring the combination with real test data.

C. Synthetic and Flight Data Combination Results

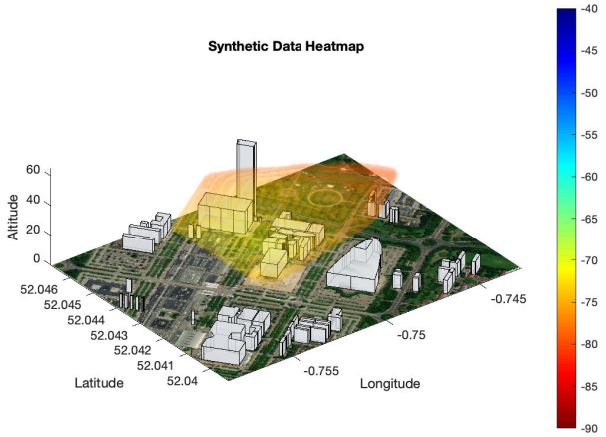
The result of 5-fold cross-validation for Area 1 is shown in Fig. 7. The coloured lines represent the flight trajectory with measured RSSI of the test set, and the 3D heatmap is the regression of synthetic data and real flight data of the training set of each fold. Each subfigure shows different trajectories and heatmaps as the training and test sets iterate through the folds. The mean RMSE is calculated as 5.1518 dB with the mean accuracy of 92.9%, which provides higher accuracy than the synthetic data only. Also, the combination with synthetic data provides RSSI in the area that the flight tests have not been conducted, indicating higher accuracy than linear or cubic extrapolation of the flight test data.

V. Conclusion

This paper proposes communication signal strength prediction and validation frameworks for the use of advanced



(a) Real test data



(b) Synthetic data

Fig. 6: Synthetic data comparison in Area 2

air mobility. The paper presents a hybrid regression-based prediction method that combines synthetic data generated from a ray-tracing model and real flight test data in urban airspace, effectively mitigating the insufficiency of flight test data. The validation framework was designed such that standardised error metrics can be provided across different maps or datasets, using k-fold cross-validation to calculate robust metrics. The results showed that the proposed framework provides reliable performance indices with higher accuracy than the ray-tracing model. This research will enable evaluating the communication infrastructure and identifying high-risk areas for advanced air mobility stakeholders.

Future work will involve more comprehensive flight tests to enhance the reliability of the proposed frameworks. The flight tests will involve not only a wider area with diverse conditions but also different environmental conditions of rain rates, humidity, and temperature. Additionally, different prediction methods, including data-driven and learning-based approaches, will be explored to improve the accuracy of the prediction.

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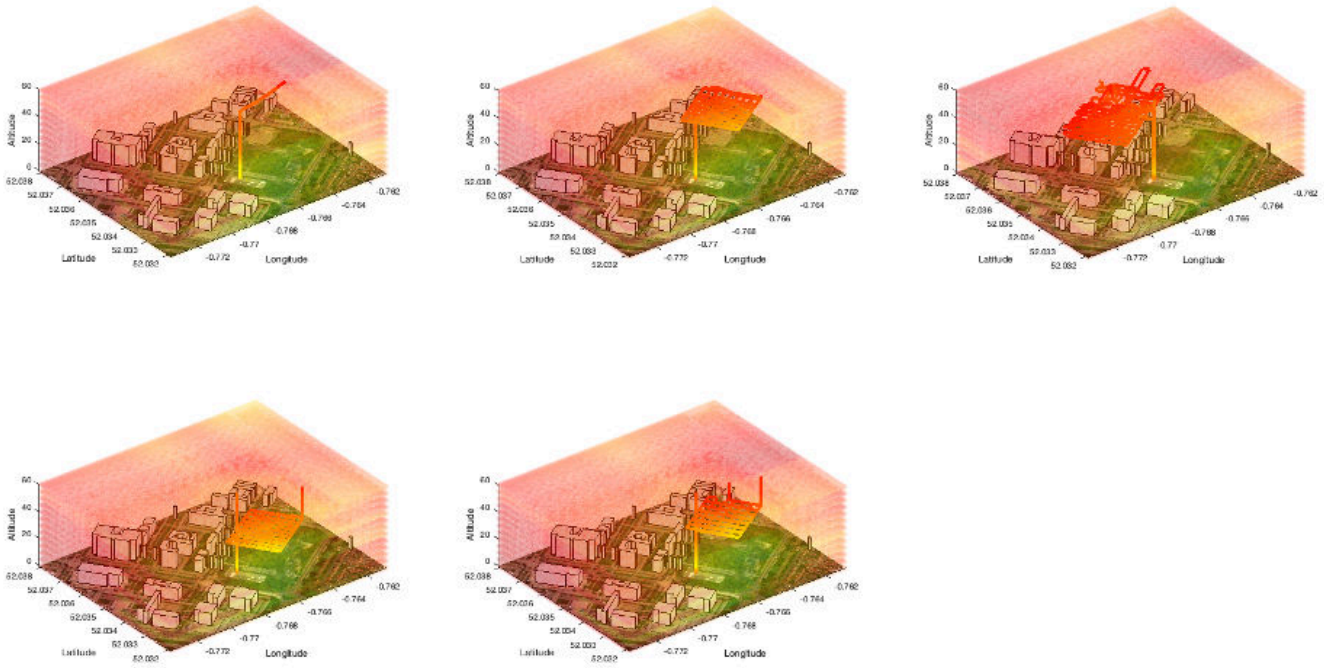

Fig. 7: 5-Fold cross-validation in Area 1

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