Characterizing 5G Interference Effects on Weather Sensors for Enhanced Spectrum Sharing in Urban Environments

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I. Introduction

The deployment of 5G wireless networks, while promising faster communication and greater connectivity, poses a significant challenge to the accuracy of weather forecasts due to potential radiation leakage into frequency bands used by weather sensors [1]. Two main focuses this summer dealt with utilizing a mobile 28 GHz IBM Phased Array Antenna Module (PAAM) to measure the effects of its transmission on a radiometer (an instrument that senses electromagnetic radiation in the atmosphere) and attempting to recreate a neural network capable of accurately predicting atmospheric data despite the presence of 5G interference. Our aim is to characterize how the interference affects the radiometer to feed into other technology we have for spectrum sharing, ultimately contributing to improved weather forecasting in dense urban environments.

II. Methodology

The methodology involved utilizing a radiometer with IBM PAAMs to conduct measurements on the rooftop of The City College of New York (CCNY), focusing on 28 GHz frequencies. Seven months' worth of datasets from CCNY, including voltage values (lvl0), brightness values (lvl1), and atmospheric readings (lvl2), specifically water vapor density levels, were provided to our lab. Initially, the variables used in the lvl0 to lvl1 equation were extracted and run to verify the accuracy of the lvl1 values. Subsequently, the data was formatted to fit a neural network model schema provided by the lab in Houston, which only shared the model attributes due to purchase constraints. A neural network model was developed, using the provided schema as a baseline. The data was split into 75% training and 25% testing resulting in about 150 days worth of training data and 50 days worth of testing data. The input matrices were of dimension 100x26, where the 100 rows corresponded to different time samples and the 26 columns represented various input features derived from the lvl1 values. The output matrices were of dimension 100x58, with the 100 rows again representing time samples, and the 58 columns corresponding to different atmospheric readings (lvl2 values) such as water vapor density levels at various elevations. To extend further from the attributes provided by the Houston schema, Cross-Validation and the Adam optimizer is used to determine an optimal amount of epochs and to train our model respectively - using the pretrained weights and biases as a starting point.

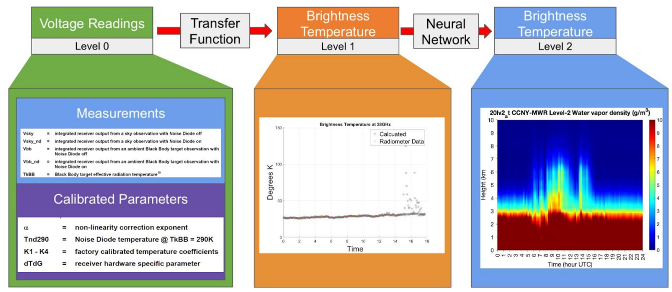

Fig. 1. lvl0 to lvl2 Function and Model Pipeline

III. Limitations

As stated in the previous section, the Houston model only provided model attributes specific to its site. This is significant because neural network models are often tailored to specific sites and conditions; thus, the model attributes alone provided a baseline, but the specific site characteristics and conditions necessitated adaptations to ensure accurate predictions. The provided neural network model schema includes 26 input nodes, 49 hidden nodes, and 58 output nodes. However, only 25 input features are specified, leaving one input variable undefined. For our study, the last input feature (25th) was copied to fill the missing 26th input.

IV. Results

The equation for converting lvl0 to lvl1 values yields a Root Mean Square Error (RMSE) of 0.0089, indicating accurate predictions of interference effects on lvl1 data. Before reconstructing the neural network model from Houston, a multi-output random forest model was used to predict lvl2 values from lvl1 inputs. This model, tested over 10 days, achieved a Mean Square Error (MSE) of 0.24, with the top features being Ch 23.0, Ch 22.5, and Ch 25.0, which aligns with results from Solheim et al [2]. The Houston neural network schema, when applied, achieved 84.48% accuracy on a day with no interference but dropped to 53.76% on a day with significant interference, highlighting the model's limitations and prompting the need to train the weights and biases specifically for our conditions. Due to the limitation of model structure information and other ongoing projects at this time (as discussed in the last section of this paper), the model is still being developed.

V. Conclusion

5G wireless network deployments have been increasing dramatically. Though they provide faster communication and greater connectivity, they pose a significant challenge to the accuracy of weather forecasts due to potential radiation leakage into frequency bands used by weather sensors. This study focused on two main objectives: utilizing a 28 GHz IBM PAAM to measure its transmission effects on a radiometer and attempting to recreate a neural network capable of accurately predicting atmospheric data despite 5G interference. Given an incomplete set of input features and suboptimal weights and biases for local conditions, we had to adjust our own model version accordingly. The results showed that the model performs well in the absence of interference but struggles with significant interference, highlighting the need for model adjustments. To address these limitations and enhance the model's performance, retraining the neural network's weights and biases using local data instead of holding the pretrained weights and biases constant must be tested. This approach aims to better accommodate the specific atmospheric conditions of New York and improve weather forecasting accuracy in dense urban environments.

VI. Side Projects

One ongoing project I am working on is an application to control the 28 GHz IBM Phased Array Antenna Modules (PAAMs), replacing the current script-based method. This interface was designed to make the complex PAAMs more accessible and user-friendly for younger audiences and other researchers - ensuring safe and straightforward operation by preventing potentially harmful inputs. Another engaging side project involved measuring radar transmission from the Army Research Lab (ARL), which recently took place. This project aimed to evaluate how spectrum management and sharing might be impacted as transmission activities increase. Understanding these effects is important for developing strategies to optimally manage and share the spectrum, particularly in dense urban environments like New York City.

References

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