Ground Level Mobile Signal Prediction Using Higher Altitude UAV Measurements and ANN

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***Abstract*—Testing the mobile network signal strength is essential for evaluating actual user experience. This procedure is done by measurement campaign, where a person or a group of people walk or drive through the target area holding a measuring equipment. However, this is not suitable to do in hard-to-reach areas. In order to minimize human involvement and to reduce resources, labour, and time consumed, an alternative approach for physical assessment of cellular coverage and quality evaluating is needed. In this work, we used a drone to measure mobile network signal strength to generate a two-dimensional coverage map for difficult-to-reach areas. A machine learning algorithm is used to estimate the signal strength in other locations within the area to generate a dense 2D coverage map. The measurements were done on Sultan Qaboos University Campus, Muscat, Oman. Our finding shows that a drone equipped with a low-cost signal strength measuring device and an artificial neural network (ANN) algorithm are able to generate an accurate dense map of mobile signal strength in a flexible and cost-effective manner. The ANN was capable of predicting the signal strength at the ground from measurement at higher altitudes with an accuracy of 97%.**

I. INTRODUCTION

Nowadays, people need a continuous access to mobile networks to do many of their daily activities. To achieve these activities, they must be provided with good mobile signal coverage. To test the quality of the received signal, network operators do periodic checks. There are several approaches to estimate the signal strength (quality of coverage) in a specific area. Examples are software using basic geographic and topographical information, network users' reports or users' complaints. However, the most dependable technique is field measurement campaigns. Huge effort is made by network operators to manage and maintain accurate records of their networks. The collected information is needed by operators to maintain the quality of their mobile coverage and for planning future project. The most common methods of collecting data in field measurement campaigns are by walking or driving. This data collection is done throughout the targeted area with the help of special measuring equipment [1]. These procedures are, however, are not suitable for hard-to-reach areas like mountainous regions.

Unmanned aerial vehicles (UAV), commonly known as drones, have attracted interest in the communication industry because of their ability to perform different tasks efficiently and cheaply. To minimize human involvement and to reduce the accidents that could happen during the measurement campaigns, especially in hard-to-reach areas, a drone can be used to collect the data.

A drone is a flying robot that can be controlled manually or autonomously along a pre-defined flight path. Drones were initially used in basic applications such as security and aerial photography. They can now even be used as "flying network nodes" to expand the network coverage and improve the system capacity [2]. Drones can cover large geographic areas that are hard to cover by traditional methods [3]

One problem to be taken into consideration while evaluating the signal strength is the high altitude of the drone with respect to the ground base. Antennas on mobile network towers are tilted down toward the ground. Signal strength at high altitudes may can be different from that at ground levels. To overcome this problem, artificial intelligence (AI) algorithms can be used to predict the signal strength at the ground given signal strength measurements at high altitudes.

Machine learning, is a subset of AI, allows learning hidden relationship between measurements that are difficult to find analytically. Among the many machine learning algorithms, deep learning achieved better than human performance in many applications [4].

In this paper, we propose a new procedure estimating mobile signal strength in a specific region using data collected by a drone and an artificial neural network. The ANN is used in this application as interpolator to generate a dense 2D mesh of mobile signal strength at the ground level using measurement obtained by the drone at a specific height from the ground. All measurement used in this paper were collected from different locations within Sultan Qaboos University campus.

The rest of the paper is organized as follows. Section II discusses related works. Section III introduced the proposed methodology and describes the datasets used in this work. The analysis is presented in Section IV. Section V presents and discusses the results. Section VI concludes the paper and proposes potential future extensions of the present work.

II. RELATED WORK

Nguyen et al [5] studied the mobile coverage availability in rural areas using a drone to record the signal strength readings at different altitudes. They found that the signal outage increases from 4.2% to 51.7% as the drone ascends to 120 m above the ground level. Amorim et al. [6] used LTE scanner connected to a drone and found that as the drone increased altitude, the radio clearance increases along with the number of detected cells.

The Reference Signal Received Power (RSRP) is used to indicate the signal strength in a particular area and to estimate the range of network availability. Nekrasov et al. [7] used different methods to collect RSRP readings. One of them is by using an application on a mobile phone attached to the drone at different altitudes. The authors found a weak relationship between the drone measurements and the ground measurements. They also categorized the RSRP into five classes that range from excellent to poor signal in terms of their strengths. The results showed that low-cost drone measurements achieved a 72% accuracy relative to the ground readings of user equipment.

Fig. 1 Location of the zones in the campus

Authors of [8] studied different estimation methods to maximize the network connectivity and provide the desired quality of service (QoS). One of these methods used ANN to enhance the design of the receiver and transmitter. The inputs to ANN were the distance, the altitude, the frequency, and the path loss. The output gave an estimate of the received signal strength. Humans and robots were located on the ground to receive the signal strength from the flying robots. Results show that the distortion of the signal can be reduced by estimating the exact signal strength and channel fading from different heights and different distances of the drone. The results showed that the prediction of the ANN was better than those produced by other methods. This was also confirmed by [9].

III. System Overview and Methodology

The measurements were carried out in 11 regions located in Sultan Qaboos University campus. Some of these regions were free space areas, while others were streets, areas close to or between buildings. Fig. 1 shows the map of SQU with the zones represented by yellow pins. Permission from the Omani Civil Aviation Authority (CCA) was obtained to fly the drone in all targeted areas. The process of collecting measurements is common for all the sites.

In this section, we describe the procedures followed to collect the required data from different altitudes and at the ground.

A. *Air Measurement Procedure*

An off-the-shelf smart phone was used to record the signal strength and the GPS locations. The smart phone is equipped with an application to read a number of LTE network parameters, such as, signal strength measurement (e.g. reference signal received power – RSRP) and save the data as an CSV file in its memory.

The altitude of the drone was fixed for each flight to study the height effect on the signal strength prediction on the ground. The DJI drone Pilot application on a tablet was used to control the desired trajectory, the speed, and the altitude of the drone throughout the experiment. The drone flew horizontally in each flight at three different altitudes (10 m, 18 m, and 24 m) while collecting signal strength readings and locations. The speed of the drone was set to be 1 m/s throughout the target area. On average, the drone took around 5 minutes to collect the needed information. The locations and received signal strength (RSS) measurements were used later as inputs to the neural network.

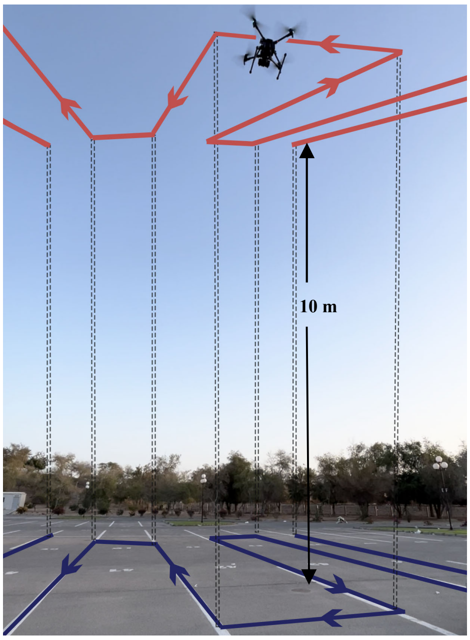


Fig. 2 Drone flight path and ground measurement path

B. *Ground Measurements Procedure*

As the drone was collecting signal strength measurement in the air, the similar path, but at the ground level, was travelled and identifying objects were placed at discrete positions along the path. Signal strength measurements were later taken at these same ground locations using the same mobile that was attached to the drone. The ground measurements were used as the target output to train the artificial neural network. Fig. 2 shows the drone path at the air and the corresponding path at the ground.

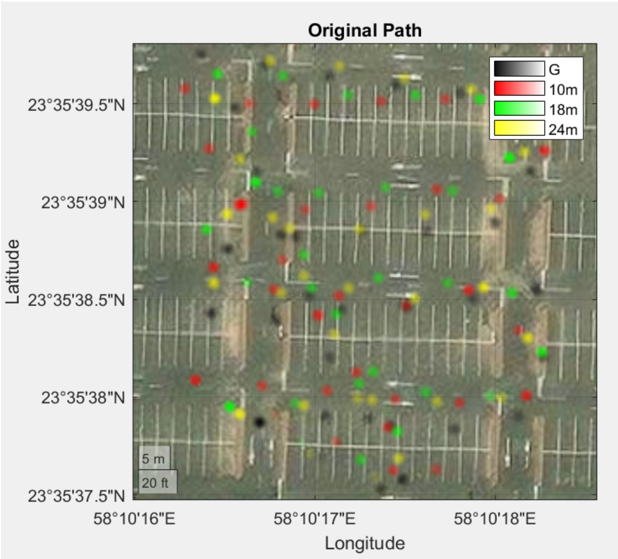
IV. Analysis

This section describes in detail the procedures used in analysing and processing the raw recorded measurements, building neural network and estimating the signal strength.

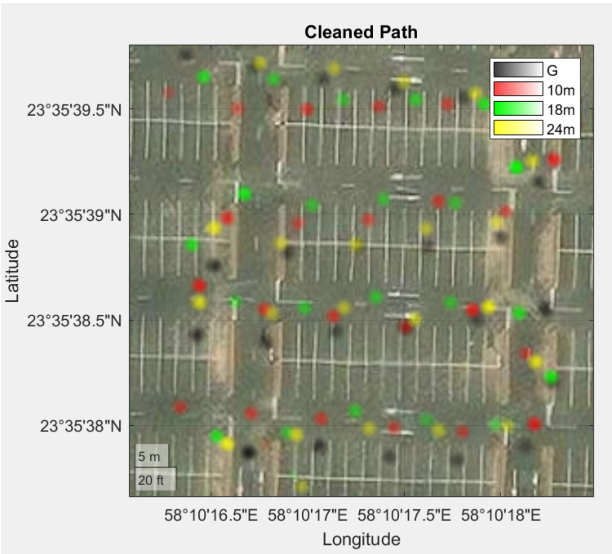
A. *Data Pre-processing*

Data collected from the ground and in the air at various altitudes (10 m, 18 m, and 24 m) has a different number of measured points. All the data were aligned based on GPS locations. Points far from the path are omitted. Although the path of the drone was pre-defined, measurements at different altitudes and ground were not necessarily at the same exact

GPS locations. Fig. 3 shows the locations where the measurements took place initially those left after the cleaning process.



(a)



(b)

Fig. 3 Measurement location (a) before and (b) after cleaning

The input and output variables of the ANN were normalized to give them equal weights to enhance the ANN accuracy and accelerate the learning process [10] [11]. In this work, we have used min-max method. To do so, the min/max equation is used. This is mathematically given by

$$X_n' = \frac{X_n - \min(X_n)}{\max(X_n) - \min(X_n)} \qquad (1)$$

where X_n is the original unnormalized variable and X_n' is the normalized one. The reverse process can be done to recover the unnormalized variable.

B. *Building Neural Network*

An artificial neural network is a collection of connected nodes. These nodes are called "artificial neurons", inspired by the human brain's neurons. ANN consists of an input layer, an output layer, and one or more hidden layers between them [12].

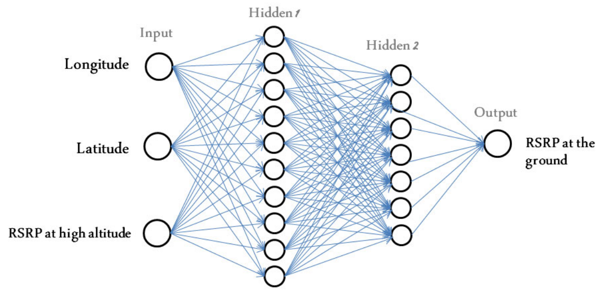


Fig. 4 Structure of the Neural Network

In our study, a neural network is needed to predict the signal strength at the ground locations given measurements and the locations of these measurements at higher altitudes. Therefore, the inputs of the ANN are the geolocation of the measurements (e.g. longitude and latitude) and the signal strength (in dBm) at these locations. A time-effective and successful prediction process can be done by using only collected measurements at one height, without the need to do multiple flights at each height. Therefore, in our work, we took measurements at different heights to study and analyse the effects of altitude on the prediction process and to find the optimal height. For these reasons, the altitude was not included in the set of input variables of the ANN but will be considered for future work. The output of the ANN is the predicted signal strength at the ground level. The collected data is divided into three sets, namely training set (70%) used for training the ANN, validation set (20%) used for preventing overfitting, and test set (10%) to assess the performance of the trained ANN. The number of epochs used in training the ANN were set at 500.

For a regression problem, the mean square error (MSE) is often used to evaluate the performance of the trained model. The target MSE of the network is set to be 0.001 in this work. Training of the model will stop when the MSE reaches the target value of or reaching number of epochs.

There is no straightforward rule for choosing the number of hidden layers and hidden neurons. Therefore, a valid viewpoint to begin with is to have a large number of neurons in the first hidden layer. Neurons on the other layers should decrease and converge to the number of neurons in the output layer [13]. For the hidden layers, we started with a single layer. The model was trained with different number of neurons each time. The number of neurons was changed from 1 to 20. For each number of hidden neurons, the Root-Mean Square Error (RMSE) of the ANN was computed. For the tested set of data, with ten neurons we achieved acceptable performance. Therefore, 10 neurons were selected for the first hidden layer. A similar process was performed for the second hidden layer. After several trial-and-error steps, a two hidden layer ANN with 10 neurons in the first layer and 7 neurons in the second layer was adopted. Fig. 4 shows the structure of the adopted ANN.

C. *Estimating Signal Strength*

Predicting signal strength with ANN can be done in two different ways: regression and classification. In the regression, the output of ANN is a continuous variable. While in the case of classification, the output is a categorical variable. In our study, we used regression, where ANN attempts to predict the exact value of RSRP, and classification, where the output is one of the four classes (quality of the coverage), namely excellent coverage, good coverage, fair coverage and poor coverage as shown in Table I.

TABLE I. SIGNAL STRENGTH QUALITY EVALUATION

RSRP Range	RSRP Quality	Color
> -90 dBm	Excellent	Green
-90 dBm to -105 dBm	Good	Yellow
-106 dBm to -120 dBm	Fair	Orange
< -120 dBm	Poor	Red

V. RESULTS AND DISCUSSION

In this section we first show the results of our approach for some locations and then assess the performance.

A. *Driving Test Approach*

Before testing our approach, we tried many scenarios to predict RSRP at locations on the ground using measurements from other locations on the ground. This was done by performing a car driving test and recording the location and RSRP readings along the path. We then tried to estimate the signal strength within the same path but at locations different from the above ones. The data was divided into three groups in the same ratio as before. The input to ANN in this case was only the location (longitude and latitude), and the output was the estimated RSRP.

To easily visualize the quality of the signal at a specific location, we plotted a map that shows the predicted RSRP after training (see Fig. 5). Based on Table I, green points represent excellent signal and yellow points represent good signal. There were no fair or poor signals in the path. A bar plot was used to compare the difference between the actual and predicted RSRP. The error histogram in Fig. 6 shows that most of the MSEs are around 0. Overall, the average percentage error was found to be 3.7%.

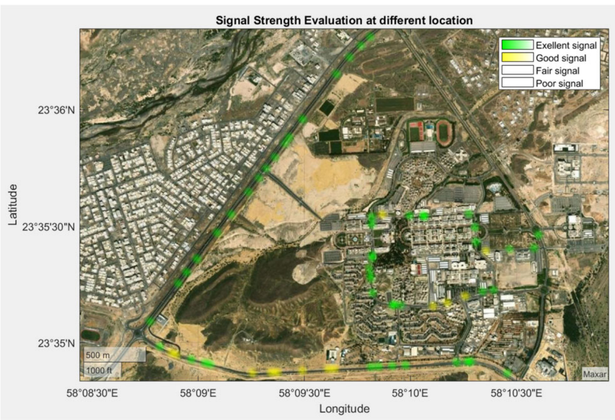
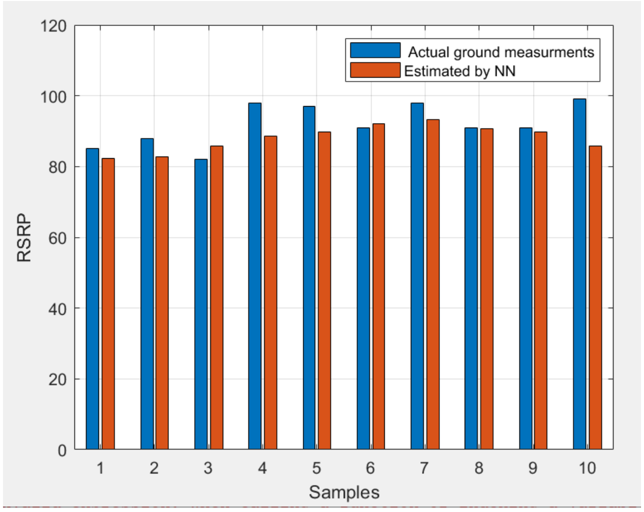
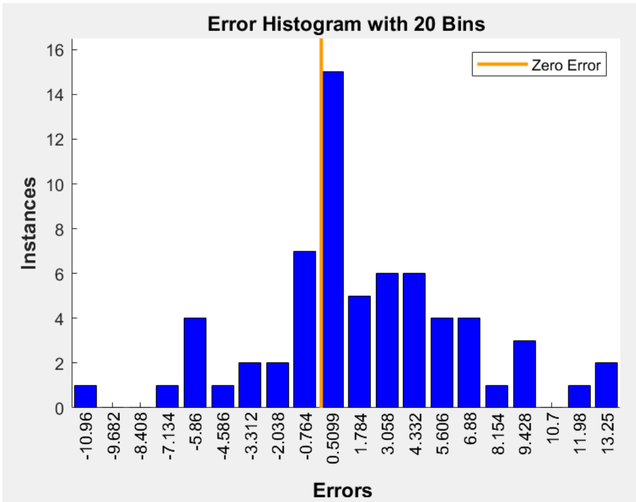


Fig. 5 Drive test evaluated coverage map



(a)



(b)

Fig. 6 Bar plots for (a) the difference between the predicted and the actual output and (b) the error histogram of the results.

B. *Drone Flight Results*

As mentioned before, measurements of RSRP from an altitude of 10 m, 18 m, or 24 m were used to estimate signal strength at the ground at the same geolocation points. Starting the training process, MSE was large at first but decreased through the training until it reached its lowest point for the validation set at epoch 108. Fig. 7 shows the learning progress of ANN.

Table II shows a sample of the test results. It represents the test set locations, the actual ground measurements, the estimated RSRPs using ANN, and the percentage error between the actual signal strength and the estimated ones. The percentage of MSE error was found to be 3.054%. The bar plot on the right shows the difference between the actual and the estimated RSS.

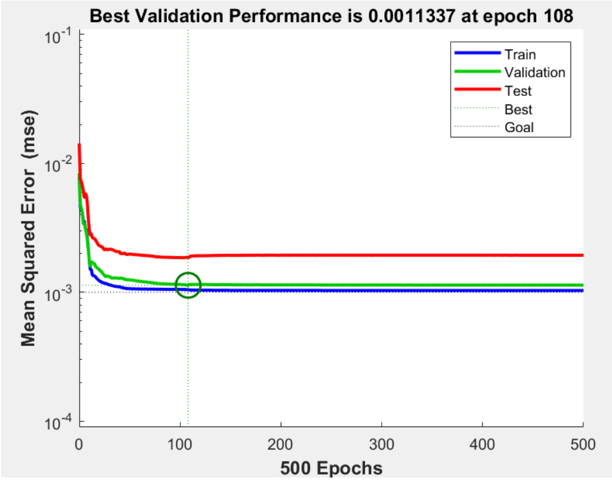


Fig. 7 MSE performance of Train, Validation and Test

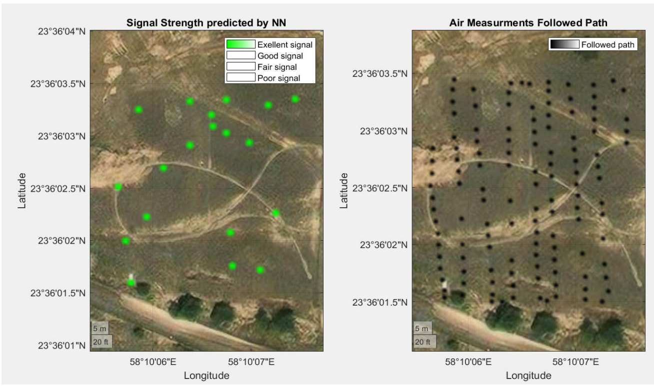


Fig. 8 Followed path by the drone and the predicted RSS

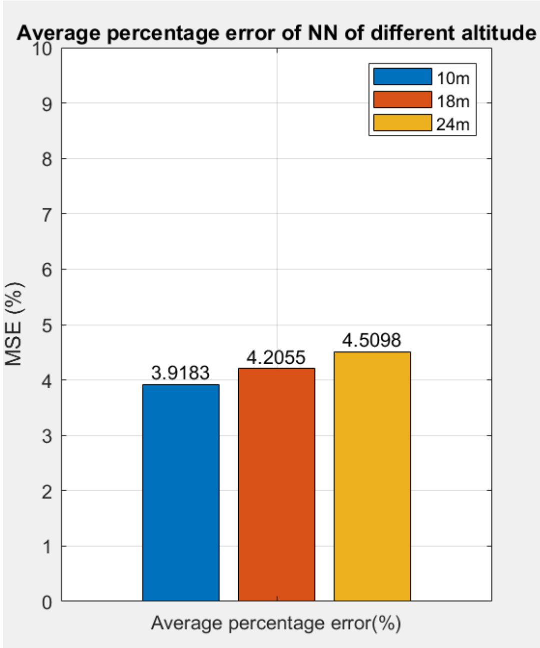
TABLE II. TEST SAMPLE RESULT AND CALCULATED ERROR

Longitude	Latitude	Actual Test RSRP	Estimated RSRP by NN	Error (%)
58.1683	23.6005	-77.1000	-75.5050	2.0687
58.1683	23.6005	-76.6000	-74.9638	2.1361
58.1683	23.6005	-76.1000	-75.8127	0.3775
58.1683	23.6007	-76.8000	-74.7034	2.7300
58.1684	23.6007	-76.0000	-76.8867	1.1667
58.1684	23.6006	-76.7000	-77.8693	1.5245
58.1684	23.6005	-77.7000	-76.6334	1.3727
58.1684	23.6008	-75.6000	-72.7632	3.7524

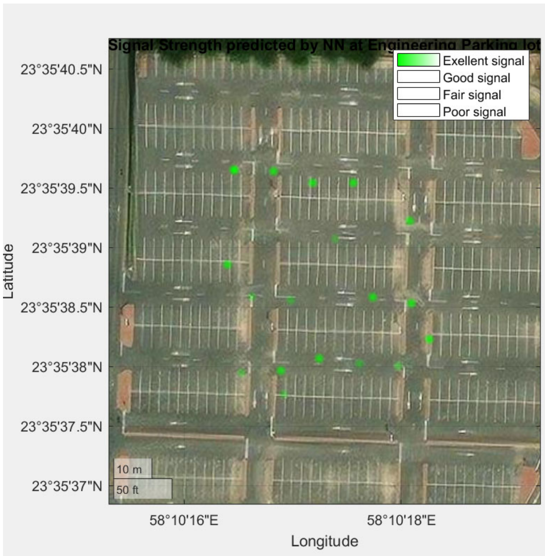
Fig. 8 shows the followed path by the drone (right) and the test batch after training (left). All points represent excellent signal levels.

C. Impact of Height

The same process was done with collected measurements at altitudes of 18 m and 24 m. For each time, only one altitude's measurements were used for training. All three altitudes show good results for predicting RSS on the ground. From the used measurements, the relationship between altitude and RSRP is found to be not straightforward.



(a)



(b)

Fig. 9. (a) MSE of estimated RSRP with three altitude measurement and (b) the output coverage map.

Therefore, predicting using measurements of the 10 m altitude shows more acceptable results since it is closer to the ground.

Many factors need to be taken into consideration when choosing the optimum altitude to predict the signal strength of the ground. One of them is to choose a path that is clear of objects that may potentially damage the drone. Therefore, we flew our drone higher than the surrounding obstacles (e.g. street lights, trees). While we couldn't fly the drone at altitudes higher than 25m, because of authority regulations, we still noticed some degradation in the signal at these altitudes in some locations.

Fig. 9(a) represents the MSE error for predicting RSRP at the ground using collected data at 10 m, 18 m, and 24 m for the same location. The coverage map of the same location using three altitude measurements for prediction looks the same as all points present excellent signal, See Fig. 9(b).

D. Impact of Location

Geographic locations and terrain nature play a vital role in predicting the signal strength. Urban areas, for example, are more complex than free-space areas because of many factors. RSS is sensitive to the effects of attenuation, reflection, diffraction, scattering, and shadowing. These factors seem to happen more in dense urban areas because of the high buildings and different obstacles. Fig. 10 and Fig. 11 show an agriculture area and a free space area, respectively. We applied NN to both locations to predict RSS on ground and to observe the impact of location on predicting signal strength. Therefore, the average MSE of agricultural location was found to be 2.82 % while that of free-space was found to be 2.4%. On average, our approach shows an accuracy of 97% for all locations despite the terrains or other characteristics of the area.

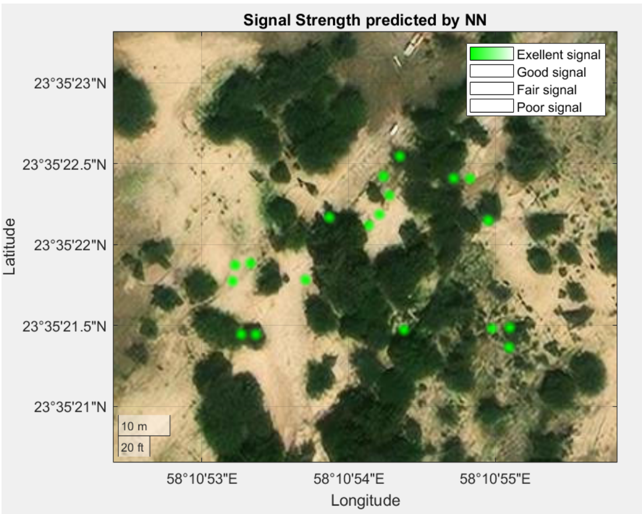


Fig. 10 Estimated RSRP on agriculture location

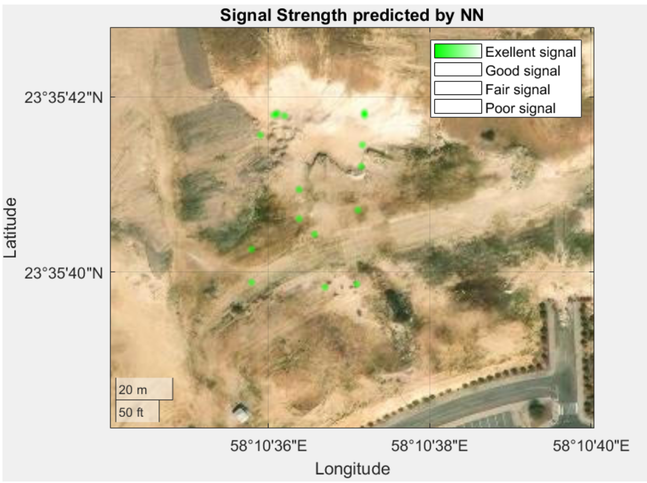


Fig. 11 Estimated RSRP on free space location

VI. Conclusion and Future Work

We have shown that signal strength can be predicted at the ground level using a neural network based on collected measurements from different altitudes. Our approach uses low-cost equipment instead of the expensive ones, and less time and labour is needed. Moreover, it's a safer choice with minimum human involvement in the field, especially when doing drive tests in hard-to-reach areas. Our findings show that ANN successfully predicted the signal strength with a mean accuracy of 97% for several locations. It was found that the average percentage error of RSS using three altitude measurements is close to each other. Therefore, measurement at 10 m altitude shows better results. Using more information to the neural network for more accurate prediction. The information can be transmitted with power from base stations, elevation angle, or calculated path loss. To expand the experiment, the same procedures can be done to predict the signal strength inside the building based on information of location and RSRP outside the building. Study of outdoor-to-indoor penetration can be considered in future work.

VII. Acknowledgment

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