Abstract—In this paper, millimeter wave (mmWave) wireless channel characteristics for Unmanned Aerial Vehicles (UAVs) assisted communication is analyzed and studied by emulating the real UAV motion using a robotic arm. The UAV motion considers the turbulence caused by the wind gusts that is statistically modelled by the widely used Dryden wind model. The frequency under consideration is 28 GHz, and the environment is an indoor type. Various power thresholds are set to find the Doppler spread experienced by the UAV hovering motion under the Dryden wind turbulence. The highest Doppler spread was found to be -102.8 Hz and +91.33 Hz at the power threshold of -50 dB. Moreover, path loss exponent of 1.62 is found with the empirical data collected during the campaign. The deep-fading case during the measurements is also further studied with another set of measurements that considers only lateral motion. The Rician fading model with a K-factor of 19.75 dB was found to best fit this channel fading model. This novel framework of emulating UAV motion will definitely help build and design future mmWave communication systems for UAVs in future.

Index Terms—mmWave, UAV, Doppler, Channel emulation, Path loss, Dryden wind, Rician fading

I. INTRODUCTION

Rapid proliferation of smart devices below 6 GHz has lead to a massive amount of data traffic, thus creating a tremendous burden on the limited frequency spectrum available to the public. To overcome this crunch, technologies such as cognitive radios [1], multiple-input and multiple-output (MIMO) [2], and non-orthogonal multiple access (NOMA) [3] etc. were proposed. However, the demand still continues to outpace the spectrum availability. In 2015, the Federal Communications Commission (FCC) released millimeter wave (mmWave) frequencies for licensed and unlicensed use. The newly licensed frequencies are 28 GHz, 37 GHz, and 39 GHz, while the unlicensed bands are 64–71 GHz [4]. Access to these mmWave frequencies allows multi gigabit wireless communication which enables fifth generation (5G) and beyond fifth generation (B5G) communications [5]. In addition to the high data rates, small antenna size, and circuits at millimeter wavelength provides reliable, highly directional and secure communication links against any eavesdropping and jamming.

On the other hand, unmanned aerial vehicles (UAVs), also referred to as drones, have seen a lot of interest from academia, industry, and from the general public at large over the past decade. The main reasons behind this large scale popularity are the ease of operability (remote or autonomous), easy deployment, higher maneuverability, and lower operating and maintenance costs of UAVs. UAVs are now extensively used in smart farming, disaster responses, military, smart logistics, and recreation (filming) [6]–[10]. Advancements in UAV technology are also fuelling the interest of its application in wireless communication technology. UAVs are capable of providing a highly reliable and cost effective mode of technology [7], [11]–[14], and can also be easily deployed as a flying base station (BS) to provide ubiquitous wireless communication access. They also provide an alternative support for 5G and B5G cellular mobile communication. Furthermore, UAVs can be used as mobile relays to provide wireless connectivity among partitioned user equipment (UE) that lack any direct line of sight (LOS) communication between the BS and UE. Apart from using as a flying BS and/or relaying node, UAVs have also found application in areas such as aerial data collectors, aerial caching, and aerial power source etc. Multiple UAVs can also coordinate, and self organise to form different network architectures, such as flying adhoc networks (FANETs), internet of drones etc. All these applications of UAV assisted wireless communication have been studied assuming Wi-Fi, or at fourth generation (4G) cellular communication frequencies. Lately, mmWave communication with UAVs have been a topic of great interest [7], [15], [16].

Recent studies [7], [15]–[19] suggest that the successful deployment of UAV-assisted mmWave wireless communication hinges on accurate and realistic propagation channel modeling. While considerable research on terrestrial propagation channels has been conducted for the last few decades, propagation channel modeling for UAVs has not been extensively studied [15]. Existing channel modeling studies mainly use 1) analytical modeling, e.g., two-ray model, or 2) ray-tracing simulations, or 3) empirical modeling using channel sounding methods. The first two methods are deterministic, cost-effective and require less effort, but they are fundamentally sub-optimal approaches given the complexity and dynamics of the wireless channels. On the other hand, empirical modeling that uses the channel sounding method could provide more realistic channel models but requires a large amount of statistical data that needs to be collected from multiple channel observations, and numerous measurement campaigns by using advanced channel sounding equipment. Moreover, microwave measurements to validate such models are inade-
quate because of fundamental differences between mmWave and microwave channels (e.g., propagation loss, directivity, sensitivity to blockage). The UAV operating environment also introduces unique atmospheric and terrain challenges \[15\]. Due to UAV restrictions (e.g., pointing, payload, power, equipment-cost constraints) and the requirement of advanced channel-sounding equipment, to our knowledge no studies have been reported that conduct empirical modeling for UAV-assisted mmWave channels. Available studies mainly use ray-tracing simulations or analytical modeling \[15\], \[19\], e.g., for frequencies of 28 GHz and 60 GHz. Also, due to differences in channel scattering environment and operating frequencies, the propagation channel models used for higher altitude aeronautical communications generally cannot be utilized directly for low altitude (small) UAV-assisted mmWave communications \[15\]. Distinct structural and flight characteristics for low-altitude UAVs could be expected such as different airframe shadowing features, and potentially sharper pitch, roll, and yaw rates of change during flight. Empirical data is therefore required to determine accurate analytic and stochastic models of mmWave wireless channels.

Utilization of a robotic arm to emulate UAV motion can 1) help overcome these challenges, 2) efficiently emulate the motion of UAV in different environments/scenarios, and 3) enable rapid collection of channel measurements by using channel sounding method to create a database for UAV-assisted mmWave channel models. In this work, a novel way to incorporate UAV motion in studying UAV assisted mmWave communication is conducted by emulating the UAV motion by utilizing a robotic arm. This method, as compared to other studies which mostly depend on the software simulation, captures the real UAV dynamics in the UAV motion. This study is an important step in realizing a real mmWave communication system for UAVs in the near future. Designing a channel emulator by using vector network analyzer (VNA) based channel sounder with real UAV motion emulated by a robotic arm to develop a first-of-its-kind, experimental, wireless channel emulator for UAV-assisted mmWave communications can produce accurate and realistic propagation channel models for a wide range of environments and scenarios. Using the robotic arm to produce atmospheric turbulence effects on UAV position and stability, we can produce the first empirical mmWave channel models that account for path loss/shadowing, Doppler spread due to UAV motion, delay dispersion (resulting in power delay profiles), and Ricean K-Factor to quantify the impact of dominant channel component.

Before, moving on to the measurement set up in the next section, it is very important to understand the different challenges associated with the mmWave communication itself. mmWave communication suffers extensively from the propagation attenuation, shadowing effect (blocking), beam misalignment’s, and Doppler shift \[17\], \[20\]–\[22\] because of small wavelength in the order of millimeter. Doppler spread effect is the most critical one, when there is a motion attributed to the movement of transmitter (Tx) or receiver (Rx) or both. In addition to that, with the wind gusts in the atmosphere for UAVs, Doppler effects are more aggravated. It is also well known that in a given mobile and multipath environment, each multipath component (MPC) will experience a different Doppler shift according to the motion. This leads to the spectral broadening at the receiver that causes erroneous signal reception or communication failure. Therefore, modeling physical UAV motion as close to a real life UAV motion is very crucial in understanding the design constraints, and performance of a mmWave based UAV communication system. Techniques to analyze and combat the Doppler effects have been studied earlier but as mentioned previously, almost all of them are based on simulations that ignore the actual UAV motion dynamics and the wind gust conditions in the atmosphere \[7\], \[13\], \[15\]. Therefore, in this paper, the focus is to analyze and study the Doppler and channel power characteristics by emulating the real UAV motion under wind gusts. The close to the real UAV motion in this work is emulated by a robotic arm in an indoor environment.

This study will: 1) empirically characterize, for the first time, the time-variant radio propagation channel of a UAV-enabled communication in mmWave range, 2) underpin novel control and aerospace designs for next-generation UAVs and UAV-assisted communications, and 3) provide the basis for channel emulators of high-complexity for next-generation communication systems. In summary, the main contributions of this paper are as follows,

- Doppler spread analysis of mmWave communication system by emulating UAV motion under the Dryden wind conditions.
- Investigation of channel power deep fade, and its relation to the UAV motion considering the wind gusts.
- Determination of path loss exponent value under indoor settings.
- Investigation of amplitude distribution assuming no orientation or angular shifts.

This paper is organized as follows, Section II discusses the measurement setup. In Section III details of the UAV motion emulation is discussed. Analysis of Doppler spread and its signal processing are presented in Section IV. Finally, Conclusions are drawn in Section V.

### II. Measurement Setup

The successful deployment of wireless communication systems requires a solid understanding and accurate modeling of wireless channel conditions (propagation characteristics) between the transmitter (Tx) and receiver (Rx). Channel sounding is a measurement technique used to gain that understanding. The channel sounding measurement method used in this study is based on continuous wave (CW) mode of VNA. The Rx is hooked up on the robotic arm, while the Tx is placed on a tripod. The Tx is positioned at different distances from the Rx (3.5 ft to 11.5 ft) depending on measurements plan. The Tx is connected at port-1 of the VNA, while the Rx is connected at port-2. At each distance point (5 points in total, with 2 feet increments between the Tx and Rx), three samples of S21 parameters are recorded on the VNA. These multiple samples of S21 parameters are recorded to get a better redundant value in the Doppler spectrum calculations, and in modelling the channel fading part. The measurement setup is
shown in the Fig. 1 and the details of all the measurement equipment used during this measurement campaign is given in Table I.

### Table I

**The Measurement Equipment with the Specifications.**

| Equipment               | Specifications                                      |
|-------------------------|-----------------------------------------------------|
| Vector Network Analyzer | Keysight PNA-X (N5247A), 10 MHz to 67 GHz           |
| Antenna (horn type)     | Cernexwave (CRA28264015), 26.5 GHz–40 GHz        |
|                         | Gain: 15 dBi, HPBW:18°                             |
| Waveguide transition    | Cernexwave (CWK28264003F), WR-28, Brass/Copper    |
| Cables                  | Fairview microwave (50 feet), Mini-Circuits (5 feet) |
| Robotic arm             | Rethink Robotics (Sawyer), software: Intera, 1 arm x 7 degree of freedom and 1 meter reach |

The VNA is operated at a frequency of 28 GHz with the intermediate frequency (IF) bandwidth set at 300 Hz. This IF frequency is selected carefully in such a way that the expected Doppler frequency can be covered within the selected IF range. In addition, a total of 4096 points were selected in this CW (carrier wave) mode. It is worth to mention that increasing the IF bandwidth will definitely decrease the time required to capture the data at each distance for a given run, however, the scattering parameter data will suffer from higher noise floor as the noise floor level is linearly proportional to the IF bandwidth. Therefore, taking multiple readings with moderate IF bandwidth was a main factor in this measurement scenario. With this selected 4096 sample points, the sampling time is, $T_s = 4.4$ ms. Thus, the Doppler range that could be captured with these settings will be in the range of $-f_s/2 = -114.49$ Hz to $+f_s/2 = +114.49$ Hz. Fig. 2 shows the actual measurement equipment and the robotic arm that were used in this measurement campaign. The Tx is at a height of 4 feet 4 inches on a tripod, while the Rx is initially at the height of 4 feet 6 inches (at the beginning point) on the robotic arm. The robotic arm is connected to a computer that executes a Python script to emulate the UAV motion with the wind turbulence model. The corresponding scattering parameter data generated under such motion is captured on the VNA, and analyzed on a workstation later on. In the next section, we will dwell more into the details on the UAV motion emulation part with the robotic arm.

### III. UAV Motion Emulation

To emulate a real UAV motion under wind turbulence is not only a very challenging but also an interesting problem. This problem can be solved by using methods from robotics area, where the real UAV motion with the wind turbulence can be easily emulated by a robotic arm. The motion of this robotic arm is controlled by robotic operating system (ROS) from a computer. To create the turbulence experienced by UAVs in atmosphere, a wind generation model is used.

The UAV motion is first simulated in MATLAB® using a stochastic wind gust model (Dryden wind model) and a 6 degree-of-freedom (DOF) quadcopter dynamic model together with closed-loop controllers are used for hovering motion models. Then, the positions and altitude of the quadcopter generated from the simulations are emulated by the end-effector (end point) of the robotic arm. The simulation framework and the arm control is briefly discussed in the following subsections.

#### A. Simulation of Quadcopter Motion with Wind

We model the wind as a combination of a 3D mean wind $(\bar{u}, \bar{v}, \bar{w})^\top$ and a 3D turbulence wind $(u, v, w)^\top$. The mean wind is specified in the north-east-down (NED) coordinates, while the turbulence wind is specified in another different frame (discussed later). In particular, the Dryden turbulence model [23], [24] is used to generate turbulence. This popular Dryden model has been extensively used for practical aviation...
applications (see e.g., [25] for its application in small fixed-wing UAV). It is based on a stochastic formulation that incorporates knowledge of the energy spectrum of turbulence [26] and assumes a homogeneous frozen spatial turbulence. The Dryden turbulence model is implemented through filtering operations on white noise signals.

Let the 3D turbulence velocity be \((u, v, w)^\top \in \mathbb{R}^3\). The \(u\) component is aligned with the direction of the horizontal mean wind, i.e., \((\bar{u}, \bar{v}, 0)\), the \(w\) component is aligned with the vertical (down) direction, and the \(v\) component is aligned with the direction that completes a right-handed coordinate frame with the \(v\) and \(w\) directions. As shown in Fig. 3, the 3D velocities \(u, v, w\) in time domain are obtained by passing three independent white noise signals through three filters described by the following transfer functions [25] Section 4.4)

\[
H_u(s) = \sigma_u \sqrt{\frac{2V_{u0}}{L_u}} \frac{1}{(s + \frac{V_{u0}}{L_u})},
\]

\[
H_v(s) = \sigma_v \sqrt{\frac{3V_{v0}}{L_v}} \frac{(s + \frac{V_{v0}}{L_v})}{(s + \frac{V_{v0}}{L_v})^2},
\]

\[
H_w(s) = \sigma_w \sqrt{\frac{3V_{w0}}{L_w}} \frac{(s + \frac{V_{w0}}{L_w})}{(s + \frac{V_{w0}}{L_w})^2},
\]

respectively, where \((\sigma_u^2, \sigma_v^2, \sigma_w^2)\) are the variances of the turbulence, \(V_{u0}\) is an estimate of the quadrotor’s airspeed, and \((L_u, L_v, L_w)\) are the turbulence length scales. In our experiments, we focus on horizontal, low turbulence effects and set \(\sigma_u^2 = 0.53, \sigma_v^2 = 0.53, \) and \(\sigma_w^2 = 0\). For low altitude, \(L_w\) is set to the altitude in feet.

In our experiments, we set \((L_u, L_v, L_w)\) to \((200, 200, 50)\) ft. Since the quadcopter is controlled in the hover mode, we set \(V_{u0}\) to be the mean wind speed, i.e., \(\sqrt{u^2 + v^2 + w^2}\), where \(\bar{u} = 2\) m/s, \(\bar{v} = -1\) m/s, and \(\bar{w} = 0\) m/s. The output of the three filters is a time-series representation of the turbulence, which is further combined with the non-zero mean wind \((\bar{u}, \bar{v}, \bar{w})^\top \in \mathbb{R}^3\). The resulting 3D wind in the NED frame is given by

\[
V_w(t) = (\bar{u}, \bar{v}, \bar{w})^\top + \mathcal{R}(u(t), v(t), w(t))^\top,
\]

where \(\mathcal{R} \in \mathbb{R}^{3 \times 3}\) is a 3D rotational matrix that converts \((u(t), v(t), w(t))^\top\) to the NED frame. The process of generating the Dryden wind is shown in Fig. 3 below.

We use a standard formulation of the quadcopter dynamics [27], with the addition of a nonlinear drag term \(f_d \in \mathbb{R}^3\) to model the wind effect. The dynamics of the quadcopter is
where \( m \) and \( (J_x, J_y, J_z) \) are the mass and the moment of inertia of the quadcopter, respectively, \((\dot{p}_n, \dot{p}_e, \dot{p}_d)\) are the north, east, and down positions in the inertial frame, \((\phi, \theta, \psi)\) are the roll, pitch, and yaw angles, respectively, \((\omega_p, \omega_q, \omega_r)\) is the angular velocity in the body frame, \((F, \tau_\phi, \tau_\theta, \tau_\psi)\) are the force and the moments in the designated directions, and \(\mathbf{f}_d = (f_{d,n}, f_{d,e}, f_{d,d})^T\) is the drag force in the north, east and down directions. The pitch, roll, and yaw axis are also shown in Fig. 4. The drag force \(\mathbf{f}_d\) is modeled in a quadratic form as

\[
\mathbf{f}_d = C_d(V_w - \hat{\mathbf{p}})[V_w - \hat{\mathbf{p}}],
\]

where \(\hat{\mathbf{p}}\) is the ground velocity of the quadcopter equal to \((\dot{p}_n, \dot{p}_e, \dot{p}_d)\) and \(C_d\) is a drag coefficient matrix.

C. Emulation of Linear Motion using the Sawyer Robotic Arm

The MATLAB software is used to generate the waypoints from the Dryden motion generation profile. In order to precisely control the velocity, the Joint Velocity Control mode was implemented in the Intera SDK. This control mode accepts velocity commands in the joint frames, not the end-effector frame, and as such the Jacobian matrix \(J(\theta_1, \theta_2, ..., \theta_7)\) is needed to translate commanded velocities between frames. Specifically, the pseudo-inverse Jacobian matrix is needed to convert velocities from the end-effector frame to the joint frames as follows,

\[
J(\theta_1, \theta_2, ..., \theta_7) = \begin{bmatrix}
\partial x / \partial \theta_1 & \partial x / \partial \theta_2 & \cdots & \partial x / \partial \theta_7 \\
\partial y / \partial \theta_1 & \partial y / \partial \theta_2 & \cdots & \partial y / \partial \theta_7 \\
\partial z / \partial \theta_1 & \partial z / \partial \theta_2 & \cdots & \partial z / \partial \theta_7 \\
\partial \phi / \partial \theta_1 & \partial \phi / \partial \theta_2 & \cdots & \partial \phi / \partial \theta_7 \\
\partial \theta / \partial \theta_1 & \partial \theta / \partial \theta_2 & \cdots & \partial \theta / \partial \theta_7 \\
\partial \psi / \partial \theta_1 & \partial \psi / \partial \theta_2 & \cdots & \partial \psi / \partial \theta_7 \\
\partial \omega_p / \partial \theta_1 & \partial \omega_p / \partial \theta_2 & \cdots & \partial \omega_p / \partial \theta_7 \\
\partial \omega_q / \partial \theta_1 & \partial \omega_q / \partial \theta_2 & \cdots & \partial \omega_q / \partial \theta_7 \\
\partial \omega_r / \partial \theta_1 & \partial \omega_r / \partial \theta_2 & \cdots & \partial \omega_r / \partial \theta_7 \\
\end{bmatrix}, \quad (6)
\]

\[
Q = J^{-1}V, \quad (7)
\]

where \(J^{-1}\) is a \(7 \times 6\) matrix representing the pseudo-inverse of the Jacobian, \(V\) is a \(6 \times 1\) matrix representing the linear and angular velocities of the end-effector, and \(Q\) is a \(7 \times 1\) matrix representing the joint velocities.

This method provides precise control of the arm’s velocity at speeds under 0.5 m/s. However, drift was introduced in the...
x-axis as the arm reached higher speeds and the end-effector reached its outer boundaries. As such, a P (proportional) controller was used to minimize the drift along the x-axis. This whole UAV motion emulation dynamic is summarized in Fig. 5. An actual snapshot of the UAV motion can also be visualized in this GitHub repository. Once the robotic arm is emulating the real UAV motion under turbulence, the next step is to measure scattering parameters from the VNA. The signal processing, and corresponding analysis to determine the Doppler spread and channel fading characteristics will be discussed in the next section.

IV. ANALYSIS OF DOPPLER SPREAD AND CHANNEL FADING CHARACTERISTICS

In this section, first the data processing of the captured VNA data (S-parameters), and its correlation with the motion profile extracted from the ROS logs, and then the analysis of Doppler spread and channel fading characteristics will be discussed in detail. Let the transmitted signal, \( x(t) = b(t) e^{j2\pi f_c t} \), where \( b(t) = x_I(t) + jx_Q(t) \) is a complex baseband signal with in-phase and quadrature components as \( x_I(t) \) and \( x_Q(t) \), and \( f_c \) is the carrier frequency. The signal \( b(t) \) is also known as the complex signal envelope or an equivalent low pass signal of \( x(t) \). Ignoring the noise in the system, the corresponding received signal with the line of sight (LOS), and all resolvable multipath is given as [30],

\[
y(t) = \Re \left\{ \sum_{n=0}^{N(t)} \alpha_n(t) b(t - \tau_n(t)) e^{j2\pi [f_c (t - \tau_n(t)) + \phi_{dn} + \phi_n]} \right\},
\]

(8)

which can be further written as,

\[
y(t) = \Re \left\{ \int_{-\infty}^{+\infty} h(t, \tau) b(t - \tau) d\tau e^{j2\pi f_c \tau(t)} \right\},
\]

(10)

where \( h(t, \tau) \) is the channel impulse response,

\[
h(t, \tau) = \sum_{n=0}^{N(t)} \alpha_n(t) e^{-j(2\pi f_c \tau_n(t) + \phi_{dn} + \phi_n)} \delta(\tau - \tau_n),
\]

(11)

where \( \alpha_n(t) \) is a function of path loss and shadowing, \( N(t) \) is the \( N \)-th resolvable multipath, \( \tau_n \) is the \( N \)-th path delay, \( \phi_0 \) is the phase offset, and \( \phi_{dn} \) is the Doppler phase shift of this \( N \)-th path. Now, when the Tx or Rx is moving, the change in the distance over a short time interval \( \Delta t \) will cause the phase to change as \( \phi_{dn} \approx 2\pi(v/\lambda)\Delta t \cos \theta \), where \( \theta \) is the arrival angle of the received signal relative to the direction of motion, and \( v \) is the velocity of receiver towards transmitter in the direction of motion. Therefore, the corresponding Doppler frequency will be then given as,

\[
f_D = \frac{1}{2\pi \Delta t} \frac{\phi_{dn}}{\lambda} \cos \theta,
\]

(12)

where \( \lambda \) is the wavelength of the signal. The data collected at VNA during the measurement campaign are the S-parameters (scattering parameters) over time (CW mode). Since the Tx is connected at port-1 and Rx at port-2, therefore, the S21 parameter will represent the channel transfer function (channel power). These S-parameters depend on time, distance and frequency. Thus, S21 parameter as a channel transfer function of time, distance, and frequency can be written as,

\[
S21_{dB}(t, f, d) = 20 \log_{10}(|H(t, f, d)|)
\]

(13)

As the VNA is set in CW time mode with frequency kept fixed at 28 GHz, the only variable in (13) would be the discrete time points at a given distance. Therefore, at a given distance \( d \), (13) can be rewritten as,

\[
S21_{dB}(t, f, d) = S21_{dB}(t)
\]

(14)

These discrete points of S21 parameter can be written in a complex vector form as, \( x[n] = S21_{dB}(t) \delta(t - t_i) \), where \( t_i \) is the discrete time point, \( \delta(\cdot) \) is the delta function, and the index \( i \) goes from 0 to 4095. Because, the S21 parameters are complex numbers, therefore, the frequency response after taking the fast Fourier transform (FFT) would also be complex in nature. Therefore,

\[
X[k] = \frac{1}{N} \sum_{n=0}^{N-1} x[n] e^{-j2\pi kn/N},
\]

(15)

where \( k \) is the point in the frequency domain, \( n \) is the point in time domain, and \( x[n] \) is the discrete time domain input (vector of all 4096 points).

Figs. 6 and 7 show an example of the S21 magnitude and phase, respectively, that was captured at a distance of 11.5 feet.
feet during this measurement process. One interesting thing to observe in Fig. 7 is the initial delay of some few seconds (∼3 seconds) before the phase significantly starts to change. This delay actually represents the time before the robotic arm actually starts to move. Also, on careful observation, one can easily observe that the initial phase offset of around -110° in Fig. 7.

A. Doppler Spread

As mentioned, in our set up, 4096 points were set in CW time mode, this number was chosen so that the Discrete Fourier transform (DFT) can be efficiently calculated by using the FFT algorithm as the data points will be in the form of $2^n$. As $N=4096$, (15) can be rewritten as follows,

$$X[k] = \frac{1}{4096} \sum_{n=0}^{4095} x[n] e^{-j2\pi kn/4096},$$

(16)

where $k = 0, 1, \ldots, 4095$. Doppler spectrum after taking the FFT of S21 parameters at a distance of 5.5 feet is shown in Fig. 8. In this work, different power threshold levels were set at -40 dB, -45 dB and -50 dB to determine the corresponding Doppler spread. These settings filters any frequency component, whose power is less than the threshold power. In Fig. 8 one can observe a lot of frequency component with high power at around 0 Hz. These frequency components at 0 Hz imply the idle or hovering motion of the UAV facing the wind gusts, which are modeled in this paper by Dryden wind model. The main parameter for the Doppler spread are the maximum positive and maximum negative frequency found in the Doppler spectrum at a defined power threshold level.

A high pass filter can also be used to remove the low frequency components around 0 Hz to observe and understand these maximum Doppler frequencies in a better way. Fig. 9 shows the frequency spectrum after the filtering operation (high pass filter) where frequencies less than 20 Hz are filtered out from the original spectrum. To completely understand the different Doppler frequencies generated during this experiment, it is very important to analyze the actual velocity profile of the UAV considering the wind turbulence model.

The ROS log files captures this very important motion dynamics. It has the details of different position of the arm end-point in 3D plane, velocity (3D), angular motion, and timestamps. It is generated in the native .bag format, which is later converted to .csv log files for processing with MATLAB software. An example of the velocity change over time of the robotic arm after processing the ROS log csv file is shown in Fig. 10. Intuitively, one can easily observe that the velocity of the UAV motion under wind turbulence doesn’t stay flat over time but changes non-linearly over the flight duration. Moreover, it can be easily seen from Fig. 10 that the time the velocity of UAV stayed in between -0.1 m/s to +0.1 m/s is more than the time it stayed out of it. Correspondingly, the probability density function (PDF) in Fig. 11 reinforces this
intuitive understanding, where the probability that the UAV stays in between -0.1 m/s and +0.1 m/s bin is more than it stays around -0.8 m/s or at 0.4 m/s.

To further reinforce this reasoning, in Fig. 12 the actual measured Doppler spectrum is plotted with the theoretical PDF, which has been scaled to fit the Doppler spectrum. As expected, the shape of the theoretical and measured Doppler spectrum is in accord with each other. The maximum positive Doppler spread (motion towards the receiver) and negative Doppler spread (motion away from the receiver) at different power threshold is listed in Table II. As expected, decreasing the power threshold will increase the Doppler spread in both positive and negative frequency side as more frequencies will be considered in the Doppler spectrum calculations.

A total of three power threshold levels of -40 dB, -45 dB and -50 dB were considered, and Doppler spectrum at each distance point was calculated, which were later on averaged out to find the average Doppler spread at that particular power threshold. These varying positive and negative Doppler spread values can be easily correlated with robotic arm motion as discussed in the previous section. This change in velocity is caused by acceleration and deceleration of UAV while facing the wind gusts that are modelled from the Dryden wind model. The maximum average Doppler spread for all distance points is at the power threshold of -50 dB, with -102.81 Hz and +91.32 Hz in negative and positive direction, while minimum Doppler spread is at -40 dB with -65.68 Hz and +30.03 Hz. These Doppler spread parameters are paramount in designing the symbol duration in a wireless communication system. Specifically, the coherence time depends on this Doppler spread, and if not properly designed for it, will result in frequency selective fading.
B. Channel Fading Characteristics

The next part is to statistically model the channel fading characteristics. As mentioned in earlier section, at each distance point, 3 samples of scattering data were recorded. An example of such 3 samples of 4096 data points appended with each other is shown in Fig. 13. The first initial points (highlighted in Fig. 13) in these S21 power samples represent no-motion or idle motion of UAV. These points can be filtered from the appended samples for each distance, and therefore, can be utilized to determine the distance dependent path loss exponent value for the indoor environment.

The path gain as a function of distance can be modelled as

\[ PG_{dB}(d) = PG_{dB}(d_0) - 10n \log_{10} \left( \frac{d}{d_0} \right) + X_\sigma(d), \]

where \( PG_{dB}(d_0) \) is the path gain at a reference distance \( d_0 \), which is 1 meter in our scenario. \( d \) is the distance between transmitter and receiver, \( n \) is the distance dependent path loss exponent, and \( X_\sigma(d) \) is the Gaussian distributed shadowing factor with zero mean in dB, and a variance of \( \sigma^2 \) in dB. The path gain as a function of distance is plotted in Fig. 14. A linear fitting model is used to find the slope of the plot which is nothing but the path loss factor \( n \). The path loss factor in our indoor scenario using this linear fitting model was found to be 1.62. On close observation of Fig. 13 where the three samples are appended with each other, one can see that there is a deep fade of around 20 dB after the no-motion samples in all three samples. It is also important to note that the half power beamwidth of the antenna is 18°, and the motion of the arm was confined in this beam space. Therefore, for this deep fade of around 20 dB, the most probable reason can be attributed to the change in the antenna orientation during the UAV motion under wind gusts. To cement this reasoning, another set of measurements were recorded with motion that doesn’t cause any change in antenna orientation.

In reality, these antenna orientation will be caused by the angular motion along the three axis-yaw, roll or pitch (Fig. 4) of a UAV under wind gusts. Fig. 15 shows the new measurement data, where 25 samples of each 4096 points are appended with each other. It can be observed that the mean power is at around -42 dB and the change caused by this controlled motion is about +/- 2 dB.

Given, there is a direct line of sight environment with many data points (25 samples of each 4096 points), the PDF would be a Rician distribution with a high K-factor. To find the close fit distribution of the channel fading (amplitude), maximum likelihood estimate is used while considering the famous distribution models of Lognormal, Rician, and Rayleigh. Fig. 16 shows the cumulative distribution function (CDF) plot of the actual data with the estimated distributions. As expected, Rician distribution comes out to be the best fit model in this scenario. The Rician PDF is given as [30], [31].


V. Conclusion

In this work, a novel mmWave channel emulation method to analyse the Doppler spread, and channel fading characteristics are presented and discussed in detail. The UAV motion was emulated by a robotic arm considering the effect of wind gusts, which was modelled by the famous Dryden wind model in this work. Different power thresholds were set to find the Doppler spread in both positive and negative frequency axis, and the maximum Doppler spread value was found to be -102.81 Hz and +91.33 Hz at the power threshold of -50 dB. No-motion data points were then selected to determine the path loss exponent for this indoor environment (laboratory), which in our scenario came out to be 1.62. In addition, the case of deep fade was studied in depth, and it was concluded that the antenna orientation is the reason behind it. This was confirmed by taking another set of measurements with only lateral motion that ignored any orientation effect. The data collected from these new set of measurements were then used to statistically model the channel fading characteristics (amplitude), and it was found out that the Rician model is the best fit candidate with a K-factor value of 19.75 dB. These results in this work will help propel the development of mmWave based UAV communication systems in the near future.

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