Statistical Blockage Modeling and Robustness of Beamforming in Millimeter Wave Systems

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Abstract

There has been a growing interest in the commercialization of millimeter wave (mmW) technology as a part of the Fifth-Generation New Radio (5G-NR) wireless standardization efforts. In this direction, many sets of independent measurement campaigns show that wireless propagation at mmW carrier frequencies is only marginally worse than propagation at sub-6 GHz carrier frequencies for small-cell coverage — one of the most important use-cases for 5G-NR. On the other hand, the biggest determinants of viability of mmW systems in practice are penetration and blockage of mmW signals through different materials in the scattering environment. With this background, the focus of this paper is on understanding the impact of blockage of mmW signals and reduced spatial coverage due to penetration through the human hand, body, vehicles, etc. Leveraging measurements with a 28 GHz mmW experimental prototype and electromagnetic simulation studies, we first propose statistical blockage models to capture the impact of the hand, human body, and vehicles. We then study the time-scales at which mmW signals are disrupted by blockage (hand and human body). Our results show that these events can be attributed to physical movements and the time-scales corresponding to blockage are hence on the order of a few 100 ms or more. Building on this fundamental understanding, we finally consider the broader question of robustness of mmW beamforming to handle blockage. Network densification, subarray switching in a user equipment (UE) designed with multiple subarrays, fall back mechanisms such as codebook enhancements and switching to legacy carriers in non-standalone deployments, etc. can address blockage before it leads to a deleterious impact on the mmW link margin.

Index Terms

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I. INTRODUCTION

The Fifth-Generation New Radio (5G-NR) wireless standardization efforts are an important component in the successful commercialization of millimeter wave (mmW) technology [2]–[5] for enhanced mobile broadband applications. In this direction, a number of (multi-institutional) efforts have focused on the scope and scale of unfavorableness in wireless propagation at mmW carrier frequencies relative to sub-6 GHz systems [6]–[10]. These studies show that while propagation losses at mmW frequencies are typically higher than with sub-6 GHz systems in both indoor and outdoor settings, these losses are not significantly worse at the mmW regime. These additional propagation losses can be overcome by array gains reaped from the use of larger antenna arrays (at both ends) [11]–[18], increased effective isotropic radiated power (EIRP) levels [19], and system design that aids in opportunistic signaling by leveraging time, frequency and space diversity [20]–[23].

Nevertheless, as the 5G-NR design process marches towards the accelerated schedule of early commercial deployments, important aspects that determine the viability of mmW technology in practice, such as outdoor-to-indoor penetration and blockage, have to be addressed carefully. Outdoor-to-indoor penetration through different types of residential/office materials has been studied extensively; see e.g., [9, Appendix E], [10]. These works report that the reflection response and penetration loss are a function of the material property, frequency, polarization and incident angle, and significantly deep signal reception notches spread over several GHz of the spectrum are observed. Such an observation motivates the need for system designs that support both frequency and spatial diversity.

In the context of spatial diversity, given the use of large antenna arrays and the diminishing beamwidths of the directional beams with antenna dimensions [15]–[18], mmW systems are

\[ \text{In particular, for non-line-of-sight (NLOS) links, [10] shows a nominal path loss degradation at 29 GHz relative to 2.9 GHz of 5.3 dB, 2.76 dB and 3.00 dB at a coverage distance of } d = 25 \text{ m in an indoor office setting, } d = 200 \text{ m in an Urban Micro setting, and } d = 100 \text{ m in a shopping mall setting, respectively. This degradation is computed as } (\text{PLE}_{29 \text{ GHz}} - \text{PLE}_{2.9 \text{ GHz}}) \cdot 10 \log_{10}(d) \text{ dB at a coverage distance of } d \text{ m where PLE}_{29 \text{ GHz}} \text{ and PLE}_{2.9 \text{ GHz}} \text{ denote the path loss exponent at the two carrier frequencies in the scenario of interest.} \]
susceptible to signal blockage much more than sub-6 GHz systems are. In particular, mmW systems are susceptible to *self-blockage*, which is shadowing from the user itself in the form of hand blocking and blockage from other body parts. This can cause a complete blockage of the user equipment (UE) antennas depending on the antenna position relative to the hand. In addition, there are blockages from the environment around the UE in the form of buildings, foliage, or other obstructions (*static blockage*) and humans, vehicles, or moving obstructions (*dynamic blockage*).

**Prior Work:** In prior work, a human blockage model has been included in the 802.11(ad) 60 GHz wireless standardization efforts [8, Sections 3.3.8, 3.5.7, 5.3.9, 8]. This model captures the probability of a cluster blockage event and the distribution function of power attenuation for these events, both via ray-tracing studies. Wideband 60 GHz human blockage measurements over a 3 GHz bandwidth has been performed in [24] and the authors study the comparative model fits between the double knife edge diffraction (DKED) and the uniform theory of diffraction (UTD) modeling frameworks showing that the DKED framework underestimates blockage loss and the UTD framework overestimates it.

The Mobile and wireless communications Enablers for the Twenty-twenty Information Society (METIS) project has proposed a human blockage model based on the DKED framework in [9, pp. 39-41, 160-162]. A blockage model is proposed by the 3GPP Rel. 14 channel modeling document [6, pp. 53-57] for mmW system modeling under two variants: a stochastic variant (Option A) and a map-based variant (Option B). Both these variants assume a 30 dB flat loss for self-blockage. A modified version of the METIS model based on 73 GHz human blockage measurements using horn antennas has been proposed to account for directional transmissions in [7], [25], [26] and these studies show that human blockage could cause signal attenuation on the order of 30–40 dB depending on the distance between the human and the transmitter/receiver. Another work that studies UE antenna modeling in form-factor UE designs at 15 GHz from a blockage consideration is [27]. This study illustrates performance losses with the hand phantom model and recommends the use of subarray diversity to overcome these losses. The readers are pointed to [28], [29] for recent studies on design tradeoffs of 5G antenna arrays with form-factor considerations.

**Contributions:** With this backdrop, we first note that most of the prior works focus specifically on human blockers in a low-mobility indoor setting with short transmit-receive distances using
horn antennas for measurements. On the other hand, the use of a phased array (2-8 antennas) at the UE end implies that the beamwidth\(^2\) at the UE side is expected to be much larger than that seen with a horn antenna. Such differences can lead to a significant variation between the blockage modeling experiments with a form-factor UE design and horn antenna measurements. In general, while form-factor UE design-based blockage modeling studies provide the gold standard in terms of understanding the implications of blockage at the UE end, such studies are currently difficult to obtain due to the still ongoing design, manufacture, development and testing of mmW technology supporting UEs/chipset solutions.

We propose to address these shortfalls by an intelligent mix of measurements with a form-factor UE prototype (as reported in [23]) and electromagnetic simulation studies for form-factor designs where such studies can supplant measurement-based insights. In particular, simulation studies are useful to understand the loss in spatial coverage with blockage. On the other hand, mmW measurements provide the best estimate for loss in signal strength as well as time-scales at which blockage disruptions happen. In this work, we provide a complementary mix of simulation studies and measurement studies for both self- and dynamic blockage.

In this direction, we first study self-blockage by considering electromagnetic simulations of antennas at 28 and 60 GHz in the proximity of the hand and identifying the spatial regions corresponding to signal blockage with different user grips. These simulation studies illustrate the blockage of a large spatial region in the UE’s local coordinate system depending on whether the UE is held in a Portrait or Landscape mode. We then study the loss incurred by the hand with different grip experiments using the 28 GHz prototype reported in [23]. In contrast to prior work that shows high self-blockage losses (30 to 40 dB), our studies show that a median loss of 15 dB is incurred by the hand even in the most pessimistic scenario of a hard hand grip. The beamwidth differences between horn antennas and a phased array design is likely to account for such wide discrepancies.

To model dynamic blockage, we conduct simulation studies to capture the impact of objects at the UE end in the form of angular regions blocked and losses incurred with a DKED model. We study the efficacy of the simulated loss data with measurement studies sing the 28 GHz

\(^2\)For example, a beam with progressive phase shifts (or a constant phase offset) over a 4 element linear array is expected to lead to a 3 dB-beamwidth of \(\approx 25^\circ\), whereas a horn antenna typically has a 3 dB-beamwidth on the order of 7.5\(^\circ\)-15\(^\circ\) at mmW frequencies.
prototype. Our studies show that though there are some discrepancies between simulated loss and true measurements, simulated data can offer a reasonable first-order estimate of blockage losses and can thus be useful for scenarios like vehicular applications, where loss estimation with measurements is considerably more complicated and difficult. These studies lead to the proposal of a statistical blockage model that has many attractive properties: i) parsimonious (captured by a small number of model parameters), ii) efficacious (captures the real impact of blockages), and iii) computationally efficient (easily useable in a system simulator framework) in studying the performance of mmW systems.

We then consider the question of time-scales at which mmW signals are disrupted due to blockage. Such time-scale estimation is important to understand the scope of mmW beamforming solutions, their robustness/stability and the nature of mitigation mechanisms to handle blockage without serious link degradation. With some prototype studies, we show that these time-scales can be attributed to physical movements of the source of blockage (hand in the case of self-blockage, humans/vehicles in the case of dynamic blockage, etc.). Thus, the dynamics of these blockers capture the time-scales at which mmW signals get disrupted and measurement studies show that they are on the order of a few 100 ms (or more). Given the sub-ms (or a few ms) effective latencies targeted by 5G-NR for beam/subarray switching, it appears that the deleterious impact of blockages can be addressed by a robust beam management procedure at the PHY layer level. In terms of PHY layer solutions, network densification, design of multiple subarrays and capability to switch beams/subarrays at the UE end, and alternate fall back mechanisms could address these challenges.

**Organization:** This paper is organized as follows. Sections II and III consider self- and dynamic blockage from both electromagnetic simulation studies and measurement perspectives, and simple statistical models are proposed to capture the effect of these blockages. Section IV considers the question of time-scales at which blockage events happen. Section V proposes multiple approaches to combat the effect of blockages and Section VI concludes the paper.

II. **Self-Blockage**

The focus of this section is on understanding the impact of self-blockage in terms of the spatial/angular coverage lost as well as the loss incurred over the blocked angles.
A. Loss in Spatial/Angular Coverage

Objects that are electrically small at microwave frequencies become electrically large at mmW frequencies, and small objects (which have the size of a few mm’s) located in the proximity of the antennas affect the antenna performance and deteriorate both their efficiencies and radiation patterns. For example, antennas placed on the display side can be affected by the liquid crystal display (LCD) shielding, LCD glass, component shields, as well as other objects such as camera(s), speaker, microphone, sensors, etc.

To investigate the effect of the antennas’ surroundings on its performance (especially its radiation pattern), the antenna module is placed over a simplified model of a UE (corresponding to a typical size of $60 \times 130$ mm$^2$) and studied in an electromagnetic simulation framework. The model of the UE simulated consists of several layers of materials: Glass with a thickness of 1 mm, LCD shielding which lies beneath the glass and extends 15 mm from the edge of the glass, and the FR-4 board with a thickness of 0.8 mm that is separated by an 8 mm air gap from the LCD shielding. Also, a battery and few shielding boxes of random sizes are placed over the printed circuit board. All the metallic objects are connected to the ground plane of the board which covers its bottom plane.

Fig. 1. A typical UE design with multiple subarrays and a hand phantom model in (a) Portrait mode and in (b) Landscape mode, along with the local coordinate system capturing azimuth and elevation angles ($\phi$ and $\theta$).

Note that “FR-4 (or FR4) is a grade designation assigned to glass-reinforced epoxy laminate sheets, tubes, rods and printed circuit boards. FR-4 is a composite material composed of woven fiberglass cloth with an epoxy resin binder that is flame resistant.” See https://en.wikipedia.org/wiki/FR-4 for more details.
For the antenna design, multiple subarray units (corresponding to placement of antennas on the Long and Top edges of the UE) in the *Portrait* and in *Landscape* modes, as illustrated in Figs. 1(a)-(b), are considered. These antenna modules are designed on a relatively low loss dielectric substrate (Rogers 4003) and are placed on the FR-4 substrate. The antenna elements are either dipole elements or dual-polarized patch elements. Antennas are designed for the respective carrier frequency and are simulated with and without hand at every azimuth and elevation angle ($\phi$ and $\theta$) in the spherical coordinate system.

To understand the impact of hand, the human hand is modelled as a homogeneous dielectric with the dielectric properties of skin tissue. In general, the skin permittivity decreases with an increase in frequency while its conductivity increases [30]–[32]. In particular, a relative dielectric
constant $\epsilon_r = 16.5$ and conductivity $\sigma = 25.8$ S/m are used at 28 GHz with CST Microwave Studio (a commercial electromagnetics simulation software suite). The hand dielectric properties determine the penetration depth into the hand and the reflection of electromagnetic waves from the hand. At the range of frequencies considered (28 and 60 GHz), the penetration depth into the hand is very small (corresponding to a high degree of reflection) ensuring a high degree of blockage by the hand.

The maximum gain of all the antennas without hand, with hand in the Portrait mode and with hand in the Landscape mode are plotted as two-dimensional contour plots (across $\phi$-$\theta$) in Figs. 2(a)-(c) for 28 GHz. From Fig. 2(a), in the absence of hand, almost the entire sphere is covered around the UE illustrating both the necessity and the goodness of the multi-subarray UE design. On the other hand, the presence of hand in either the Portrait or Landscape modes adversely affects the radiation coverage as seen from the blue areas (defined as signal strengths below $-5$ dBi) in Figs. 2b)-(c). The region in blue stretches from behind the palm to the thumb (associated based on the corresponding $\phi$-$\theta$ angles). Furthermore, it is seen that the long edge module does not play an important role in signal reception in the Portrait mode as it is blocked with the fingers resulting in significantly deteriorated antenna efficiencies. On the other hand, the short edge is not affected much with the presence of the hand ensuring that diversity from subarrays is critical for seamless communications. For the Landscape mode, the antennas along the long edge are unobstructed leading to better coverage than the short edge antennas.

While the electrical properties of the hand are different between 28 and 60 GHz, the hand still acts as a lossy reflector and can severely deteriorate antenna performance. In general, the skin permittivity and conductivity decreases and increases with frequency, respectively. Based on [30]–[32], a relative dielectric constant of $\epsilon_r = 7.9$ and conductivity of $\sigma = 36.4$ S/m are used at 60 GHz and simulations (as above) are redone. Figs. 2(d)-(f) plot the coverages without hand, with hand in the Portrait and Landscape modes, respectively, for 60 GHz. Compared to 28 GHz, at 60 GHz, the electrical size of the UE and hand are almost doubled while the antenna size is approximately reduced to half. This prevents the radiation of the antennas located on the top and left sides to leak to the right or bottom sides of the UE. Thus, even in the absence of hand, complete radiation coverage around the UE is quite challenging (as seen from the streaks

\[\text{Note that the heat map adjacent to the gain plots illustrate the strength of signal coverage.}\]
of blue without the hand in Fig. (d).

In the Portrait mode in Fig. (e), the left edge of the phone is obstructed by the fingers which causes blockage on the left side as well as back side of the hand. This forms a dead zone between 60° to 110° from the Z-axis, which is perpendicular to the hand. The high gain radiation coverage occurs in front of the phone due to radiation from the patch antennas located at the top edge. In comparison, the back of the phone which is illuminated by the top edge dipoles shows slightly lower gain. In the Landscape mode in Fig. (f), while neither subarray at the UE is blocked severely, the hand still prevents the top edge dipoles to radiate towards the back of the hand and most of the radiation is reflected or absorbed.

B. Loss in Signal Strength

The blockage loss incurred by the hand in the studies of Sec. II-A are plotted in Fig. (a) [see curves grouped as “Simulations”]. In particular, the cumulative distribution function (CDF) of the maximal gain from all the antennas in both polarizations is compared between the Freespace mode (without the hand) and Portrait/Landscape modes (with hand) and plotted here. These studies show that the loss appears to be in the range of −5 to 15 dB (with negative values corresponding to signal energy boosting due to hand reflection at certain angles). In particular, Fig. (a) shows that blockage loss is possible for up to 70% and 50% of the angles in Portrait and Landscape modes, respectively. However, these estimates are sensitive to the hand phantom model used in the simulation studies (see Fig. 1). In particular, the tightness of the hand grip around the UE determines what fraction of electromagnetic energy is captured by the antennas with a tighter/harder grip leading to significant losses (and vice versa). The nature of the air gap between the fingers also determines what fraction of energy is captured as multiple reflections from the skin surface, which can assist signal reception in certain angles. Thus, while the above simulation studies could be used for studying loss in angular coverage, using them directly for loss in signal strength could be questionable.

In this context, some measurement studies from [7], [25], [26] suggest a loss of even up to 30 to 40 dB with hand and body blockage. However, all these measurements are based on the use of horn antennas and cannot be extended easily to form-factor UE designs. To understand the loss possible with the hand, measurement studies are performed with a 28 GHz experimental prototype capturing the attributes of a 5G base-station as well as a form-factor UE design and
operating in a time-division duplexing framework. With this prototype, the baseband analog in-  
phase and quadrature (IQ) signals are routed to/from the modem to an IQ modulator/demodulator  
at 2.75 GHz center frequency. The 2.75 GHz intermediate frequency signal is translated to 28  
GHz using a 25.25 GHz tunable local oscillator (with a 100 MHz step size). The base-station  
end of this system is a 16 × 8 planar array (made of a waveguide design) that allows analog  
beamforming using tunable four bit phase shifters and gain controllers. The UE end is a form-  
factor design made of four selectable subarrays, each a four element phased array of either  
dipoles or patches with locations on the UE as illustrated in Fig. 1(a). More details on the  
design parameters of the prototype are provided in [23].

In our hand loss studies, the form-factor UE is grabbed by the hand at normal speed and the  
hand completely covers/envelops the active antenna arrays as illustrated in Fig. 3(b). All the  
subarrays at the UE side except the enveloped subarray are disabled in terms of beam switching  
thus allowing us to capture the blockage loss in terms of received signal strength differentials. We  
define an RF event relevant for these studies as one where the received signal strength indicator  
(RSSI) drops from the steady-state value by at least 2 dB. From our experiments, 38 such RF  
events are recorded and for each RF event, ten RSSI minimas spanning the entire event are  
separately recorded. The link degradation is computed as the RSSI difference between the steady-  
state RSSI value and the ten minimas. The empirical CDF of hand blockage loss corresponding  
to these 380 data points is also plotted in Fig. 3(a) [grouped under “Measurements”]. From this  
plot, we note that observations of 30-40 dB hand blockage loss from [7], [25], [26] may be  
too pessimistic to capture real measurements based on form-factor UE designs. More reasonable  
estimates for hand blockage loss are on the order of 5-20 dB with a median loss of 15 dB.

We now consider a number of model fits for the hand blockage loss data. The efficacy of each  
model (for the loss data) is captured by the Kolmogorov-Smirnov (KS) distance [33], defined  
as,

\[
 d_{KS}(\text{data, model}) \triangleq \max_x \left| F_{\text{data}}(x) - F_{\text{model}}(x) \right|,
\]

where \( F_{\text{data}}(x) \) and \( F_{\text{model}}(x) \) denote the CDFs with the empirical data and the corresponding  
model, respectively. Since the KS distance only captures the worst-case deviation between the

\footnote{Due to constraints on the post-processing of data, RSSI minimas can be recorded to only within a 1 dB precision.}
two CDFs, we also consider a data-weighted KS (WKS) distance, defined as,

\[ d_{WKS}(\text{data}, \text{model}) = \int x \cdot |F_{\text{data}}(x) - F_{\text{model}}(x)| \cdot dx. \]

A better model fit for the data is captured by smaller KS and WKS distances (and vice versa).

**TABLE I**

| Model                        | Parameters | \(d_{KS}\) | \(d_{WKS}\) | \(d_{KS}\) | \(d_{WKS}\) |
|------------------------------|------------|-------------|--------------|-------------|--------------|
| **Hand blockage**            |            |             |              |             |              |
| Gaussian: \(1 \sqrt{2\pi\sigma^2} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}}\) | \(\mu = 15.26, \sigma = 3.80\) | 0.19 | 1.22 | \(\mu = 8.54, \sigma = 2.45\) | 0.17 | 0.46 |
| Weibull: \(\frac{\beta}{\alpha} \cdot (\frac{x}{\alpha})^{\beta-1} \cdot e^{-\frac{x}{\alpha}}\) | \(\alpha = 16.70, \beta = 4.61\) | 0.17 | 1.16 | \(\alpha = 9.43, \beta = 3.94\) | 0.16 | 0.45 |
| Gaussian mixture: \(\frac{p_1}{\sqrt{2\pi\sigma_1^2}} \cdot e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}} + \frac{1-p_1}{\sqrt{2\pi\sigma_2^2}} \cdot e^{-\frac{(x-\mu_2)^2}{2\sigma_2^2}}\) | \(p_1 = 0.75, \mu_1 = 16.28, \sigma_1 = 1.71, p_2 = 0.25, \mu_2 = 12.15, \sigma_2 = 6.03\) | 0.26 | 1.51 | \(p_1 = 0.11, \mu_1 = 3.23, \sigma_1 = 0.42, p_2 = 0.89, \mu_2 = 9.17, \sigma_2 = 1.70\) | 0.21 | 0.62 |
| Gaussian Weibull mixture: \(\frac{p_1}{\sqrt{2\pi\sigma_1^2}} \cdot e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}} + \frac{(1-p_1) \beta}{\alpha} \cdot (\frac{x}{\alpha})^{\beta-1} \cdot e^{-\frac{x}{\alpha}}\) | \(p_1 = 0.15, \mu_1 = 15.76, \sigma = 3.55, p_2 = 0.85, \alpha = 17.20, \beta = 6.11\) | 0.14 | 0.70 | \(p_1 = 0.15, \mu_1 = 9.54, \sigma = 1.95, p_2 = 0.85, \alpha = 9.43, \beta = 3.69\) | 0.15 | 0.39 |

Fig. 3. (a) CDF of hand blockage loss with electromagnetic simulations using a hand phantom model, measurements using the experimental prototype, and model fits to measurement data. (b) Pictorial illustration of the hand holding experiment with the UE where the hand covers/envelops the active antenna array completely.
The empirical mean and empirical standard deviation of the hand blockage loss data are 15.26 dB and 3.80 dB, respectively. The functional forms as well KS and WKS distances of the different models considered here are presented in Table I. In terms of the models, we first consider a Gaussian density with mean and standard deviation being the empirical mean and empirical standard deviation values (as above). This model fit is plotted in Fig. 3(a). From this plot, we observe that the Gaussian density over-estimates both the lower and upper tail values of loss and under-estimates the bulk. That is, the measured data has a heavier lower tail than the Gaussian density can fit. This mismatch is also reflected in the high KS and WKS distances with this model (see Table I). To overcome this problem, we consider a Weibull density that is typically used to model heavy tailed data. While the Weibull density improves the KS and WKS distances, from Fig. 3(a) as well as Table I we see that there is no dramatic improvement in fit with this model. Note that both these models are described by two parameters.

For a better fit, we therefore consider models with more parameters. While different model families can be considered, we start with a Gaussian mixture with the hope that these Gaussians can individually capture the upper and lower tails better. The parameters for the Gaussian mixture are learned using the Expectation Maximization algorithm as described in Appendix A. In contrast to the expectation, our results show that the best Gaussian mixture model fails to capture the data accurately as the tails of one Gaussian component lead to a poor fit for the other Gaussian component (and vice versa). In fact, the Gaussian mixture leads to a good fit only at the bulk. To remedy this misfit, we consider a Gaussian-Weibull mixture model as an alternate candidate. Since an analogous Expectation Maximization solution (as in Appendix A) appears to be difficult due to the complicated structure of the Weibull density, we use a local search over the parameter space neighborhood initialized with the individual Gaussian model and Weibull model parameters, respectively. The objective of this optimization is to minimize the WKS distance of the consequent model fit. As observed from both Fig. 3(a) and Table I

6Theoretically, a Gaussian approximation to the loss can result in a value that is negative due to the Gaussian tail. Independent of whether negative loss values make sense, for all practical purposes, such realizations are not seen in numerical studies due to the extremely low probability of such occurrences. Thus, we will not bother with these technical difficulties in this paper.

7Note that the Weibull density $W(\alpha, \beta)$, where $\alpha$ and $\beta$ are the scale and shape parameters, is commonly used to model “time-to-failure” of a certain process with $\beta$ capturing the failure rate of the process. In particular, $\beta < 1$, $\beta = 1$ and $\beta > 1$ capture decreasing, constant, and increasing failure rates of the process with time.
the optimized Gaussian-Weibull mixture fits the empirical data better suggesting its utility as a generative model for hand blockage loss.

C. Proposed Statistical Model

Based on the studies in Sec. II-A and II-B, we propose a simple square region approximation for spatial/angular blockage with the hand. This approximation is captured by the center of the blocker ($\phi_1$, $\theta_1$), and the angular spread of the blocker ($x_1$, $y_1$) in azimuth and elevation with the blocking angles captured as $\phi \in [\phi_1 - \frac{x_1}{2}, \phi_1 + \frac{x_1}{2}]$ and $\theta \in [\theta_1 - \frac{y_1}{2}, \theta_1 + \frac{y_1}{2}]$ in azimuth and elevation, respectively. For the blockage loss, we propose a low-complexity variant captured by the Gaussian fit and a relatively higher-complexity variant captured by the Gaussian-Weibull mixture fit from Table I. These proposals lead to the statistical model in Table II (in the local coordinate system around the UE) for self-blockage.

| Scenario           | $\phi_1$ | $x_1$ | $\theta_1$ | $y_1$ | Blockage loss (in dB)                           |
|--------------------|----------|-------|-------------|-------|------------------------------------------------|
| Portrait mode      | $260^\circ$ | $120^\circ$ | $100^\circ$ | $80^\circ$ | Low-complexity : $\mathcal{N}(\mu = 15.3 \text{ dB}, \sigma = 3.8 \text{ dB})$ |
| Landscape mode     | $40^\circ$ | $160^\circ$ | $110^\circ$ | $75^\circ$ | High-complexity : Gaussian-Weibull mixture with $p_1 = 0.15$, $\mu = 15.8$, $\sigma = 3.6$, $p_2 = 0.85$, $\alpha = 17.2$, and $\beta = 6.1$ |

III. Dynamic Blockage

A. Methodology for Modeling Dynamic Blockage

We assume that the dominant signal path(s) between the transmitter (base-station) and the receiver (UE) are in the plane connecting them. In outdoor use-cases where the transmitter is on the top of a building or a lamp post, as well as indoor use-cases where the transmitter is on/near the ceiling or at the same level as the receiver, such an assumption is reasonable with at least

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8Nevertheless, this assumption significantly simplifies the study done in this work and should be treated as a first attempt at a comprehensive statistical model for blockage. Future studies will consider further extensions of the setup considered in this work.
moderate cell sizes. We now propose a simple methodology to capture the impact of dynamic blockers (e.g., humans, vehicles, etc.) that are strewn randomly in the transmit-receive plane.

Relative to a global coordinate system, the azimuth angle of the blockers are assumed to be uniform in $[0^\circ, 360^\circ)$ and the elevation angle is assumed to be a fixed $\theta_o$. Without loss in generality, we assume that $\theta_o = 90^\circ$ (that is, the transmit-receive plane is the horizontal plane). If the blockers are too close to either the transmitter or the receiver, the observed blockage loss can be significant. At the receiver end, such a scenario is already captured by the self-blockage component and at the transmitter end, it is less likely provided the transmitter has a reasonable unobstructed coverage (the precise scenarios considered in this work).

To capture these aspects explicitly, as illustrated in the top-view of the transmit-receive plane in Fig. 4(a), the blockers are assumed to lie in a circular region (with radial locations $r$ constrained as $d_{\text{min}} \leq r \leq d_{\text{max}}$) around the receiver. A triangular density function of the form

$$f(r) = \frac{2 (r - d_{\text{min}})}{(d_{\text{max}} - d_{\text{min}})^2}, \quad d_{\text{min}} \leq r \leq d_{\text{max}}$$

is assumed for $r$. This density captures the fact that the blocker density grows with $r$ since there is more area covered by the circular region with $r$ closer to $d_{\text{max}}$ than at $d_{\text{min}}$. The heights and widths of the blockers are modeled as $h \sim U([H - h, H + h])$ and $w \sim U([W - w, W + w])$ where $U([a, b])$ stands for a uniform random variable over the interval $[a, b]$, $H$ and $W$ denote the mean height and width of the blocker, and $h$ and $w$ denote the one-sided deviations for the height and width of the blocker, respectively.

We propose to model the number of blockers in the region of interest as a Poisson random variable with parameter $\lambda$. That is,

$$\mathbb{P}(\text{No. of blockers} = k) = \frac{\lambda^k}{k!} \cdot e^{-\lambda}, \quad k = 0, 1, 2, \cdots$$

Let the average density of blockers be defined as the number of blockers per unit area. With the model from Fig. 4(a), the average density of blockers is given as $\frac{\lambda}{\pi (d_{\text{max}}^2 - d_{\text{min}}^2)}$. For simplicity, the blocker and the receiver are assumed to be parallel in orientation and the angle subtended at the receiver/UE by the blocker is computed as $\sin \left(\frac{\phi}{2}\right) = \frac{w}{r}$ and $\sin \left(\frac{\theta}{2}\right) = \frac{h}{r}$ in azimuth and elevation, respectively.

\footnote{Since the distances tend to be small for both indoor and outdoor use-cases, approximations such as $\phi = \frac{w}{r}$ and $\theta = \frac{h}{r}$ can be inaccurate.}
To study the loss in spatial/angular coverage, we use the parameters from [7]: $H = 1.7$ m and $W = 0.3$ m for human blockers, and $H = 1.4$ m and $W = 4.8$ m for vehicular blockers. For modeling human and vehicular variations, we also use $h = 0.2$ m and $w = 0.1$ m for humans, and $h = 0.4$ m and $w = 0.5$ m for vehicles. In a typical indoor office setting such as the third floor of the Qualcomm building, Bridgewater, NJ with dimensions of $75 \times 40$ sq m and occupied by 50 to 100 humans, the average density of human blockers ranges from 0.0166 to 0.0333 per sq m. Similarly, in a typical outdoor setting of $100 \times 100$ sq m with 10 to 50 vehicles, the average density of vehicular blockers could range from 0.001 to 0.005 per sq m. For three choices of $\lambda$ and $d_{\text{max}}$, Table III presents the average density of human and vehicular blockers in the indoor

| Human ($d_{\text{min}} = 3$ m) | $\lambda = 4$ | $\lambda = 8$ | $\lambda = 12$ | Vehicular ($d_{\text{min}} = 5$ m) | $\lambda = 4$ | $\lambda = 8$ | $\lambda = 12$ |
|---------------------------|--------------|--------------|---------------|-----------------------------|--------------|--------------|---------------|
| $d_{\text{max}} = 10$ m  | 0.0140       | 0.0280       | 0.0420        | $d_{\text{max}} = 30$ m    | 0.0015       | 0.0029       | 0.0044        |
| $d_{\text{max}} = 15$ m  | 0.0059       | 0.0118       | 0.0177        | $d_{\text{max}} = 40$ m    | 0.0008       | 0.0016       | 0.0024        |
| $d_{\text{max}} = 20$ m  | 0.0033       | 0.0065       | 0.0098        | $d_{\text{max}} = 50$ m    | 0.0005       | 0.0010       | 0.0015        |

TABLE III

AVERAGE DENSITY OF BLOCKERS WITH DIFFERENT $d_{\text{max}}$ AND $d_{\text{min}}$
and outdoor cases, respectively. For a human blocker, we assume $d_{\text{min}} = 3$ m and three cases for $d_{\text{max}}$: $d_{\text{max}} = 10, 15,$ or $20$ m (denoted as Cases 1-3). For a vehicular blocker, we consider $d_{\text{min}} = 5$ m and three cases for $d_{\text{max}}$: $d_{\text{max}} = 30, 40,$ or $50$ m (also denoted as Cases 1-3). While different choices of $\lambda$ can be considered in general, from Table III we focus on $\lambda = 4, 8, 12$ as representative samples to reflect average density of blockers in typical indoor and outdoor deployments.

B. Loss in Spatial/Angular Coverage and Number of Blockers

Table IV presents the median, 90th and 95th percentile values of the mean angular blockage in azimuth and elevation for $\lambda = 4, 8$ and $12$. From these studies, we note that the mean spatial/angular blockage for both human and vehicular blockers decreases as $d_{\text{min}}$ increases or $d_{\text{max}}$ increases. This is because the blockers are farther away from the receiver as $d_{\text{min}}$ increases and are more likely to be farther away from the receiver as $d_{\text{max}}$ increases. In either case, a smaller angle is casted at the receiver leading to a reduction in the mean angular blockage. Further, this angle has only a weak dependence on $\lambda$. We conclude that a typical mean angular blockage of $2.5^\circ$ in azimuth and $15^\circ$ in elevation are seen with human blockers, and $15^\circ$ in azimuth and $5^\circ$ in elevation are seen for vehicular blockers.

We are now interested in understanding the number of blockers $K$ to be incorporated in a statistical model for dynamic blockage. Table V presents the explanatory power captured by the fraction of the total azimuthal angular blockage captured by the top-$K$ blockers. The median, 90th and 95th percentile values of the explanatory power are presented for human blockers with $d_{\text{min}} = 3$ m, $d_{\text{max}} = 15$ m, and for vehicular blockers with $d_{\text{min}} = 5$ m, $d_{\text{max}} = 40$ m for different choices of $\lambda$. Table V shows that there is a decreasing explanatory power for a fixed $K$ as $\lambda$ increases, and diminishing returns and increasing model complexity with an increase in $K$ for any $\lambda$. The use of the top-4 human and top-3 vehicular blockers can explain over 60% of the blocked angular region up to $\lambda = 8$ and suggests a good tradeoff point/compromise between explanatory power and model complexity.

While we consider the top-$K$ blockers in terms of angles blocked, alternate criteria such as top-$K$ blockers in terms of blockage loss can also be considered. The flavor of the results are not expected to change with such alternate criterion.
### TABLE IV

**Angular Blockage Metrics with Human and Vehicular Blockers**

|         | Mean angular blockage (Human) | Mean angular blockage (Vehicular) |
|---------|-------------------------------|-----------------------------------|
|         | Azimuth (in degrees)          | Elevation (in degrees)            |
|         | Azimuth (in degrees)          | Elevation (in degrees)            |
| Percentiles | 50 | 90 | 95 | 50 | 90 | 95 | 50 | 90 | 95 | 50 | 90 | 95 |
| Case 1  | 2.34 | 3.00 | 3.26 | 13.19 | 16.34 | 17.55 | 14.27 | 20.50 | 23.14 | 4.02 | 5.71 | 6.41 |
| Case 2  | 1.65 | 2.24 | 2.48 | 9.31 | 12.32 | 13.54 | 10.80 | 16.00 | 18.31 | 3.07 | 4.53 | 5.19 |
| Case 3  | 1.28 | 1.80 | 2.03 | 7.21 | 9.95 | 11.10 | 8.74 | 13.14 | 15.19 | 2.50 | 3.78 | 4.36 |
| Case 1  | 2.40 | 2.88 | 3.05 | 13.44 | 15.57 | 16.32 | 15.69 | 20.98 | 23.06 | 4.25 | 5.54 | 6.03 |
| Case 2  | 1.71 | 2.11 | 2.26 | 9.60 | 11.62 | 12.37 | 11.79 | 15.88 | 17.47 | 3.27 | 4.37 | 4.81 |
| Case 3  | 1.33 | 1.69 | 1.83 | 7.47 | 9.36 | 10.10 | 9.48 | 12.81 | 14.18 | 2.66 | 3.63 | 4.02 |

### TABLE V

**Explanatory Power of the Top-\(K\) Blockers**

| Percentiles | \(\lambda = 4\) | \(\lambda = 8\) | \(\lambda = 12\) |
|-------------|------------------|------------------|------------------|
| Top-2       | 64.54%           | 39.12%           | 29.37%           |
| Top-3       | 84.51%           | 53.42%           | 40.41%           |
| Top-4       | 100.00%          | 65.96%           | 50.20%           |
| Top-5       | 100.00%          | 77.27%           | 59.06%           |
| Top-6       | 100.00%          | 86.94%           | 67.18%           |
| Human       | 42.16%           | 27.66%           | 21.45%           |
|             | 38.04%           | 25.31%           | 19.78%           |
|             | 39.12%           | 25.31%           | 21.45%           |
|             | 35.72%           | 28.15%           | 28.15%           |
|             | 45.14%           | 35.75%           | 35.75%           |
|             | 53.83%           | 42.76%           | 42.76%           |
|             | 61.85%           | 49.29%           | 49.29%           |
| Top-2       | 70.18%           | 47.48%           | 39.44%           |
| Top-3       | 100.00%          | 63.33%           | 52.94%           |
| Top-4       | 100.00%          | 76.34%           | 64.28%           |
| Top-5       | 100.00%          | 88.29%           | 73.97%           |
| Top-6       | 100.00%          | 100.00%          | 79.79%           |
| Vehicular   | 46.48%           | 43.40%           | 29.14%           |
|             | 42.12%           | 31.51%           | 26.96%           |
|             | 47.48%           | 31.51%           | 26.96%           |
|             | 44.08%           | 37.86%           | 37.86%           |
|             | 50.82%           | 47.56%           | 47.56%           |
|             | 59.78%           | 56.24%           | 56.24%           |
|             | 64.93%           | 61.52%           | 61.52%           |
Fig. 5. (a) CDF of human body blockage loss with simulations using the dynamic blockage methodology, measurements using the experimental prototype, and model fits to measurement data. (b) CDF of human body and vehicular blockage loss with simulations using the dynamic blockage methodology.

C. Loss in Signal Strength

For the human body blockage loss, we use the DKED model from [7], [34], [35] with $d_{\text{min}} = 0.5$ m, $\lambda = 4$ and the transmit-receive distance $R = 20.5$ m. Fig. 5(a) plots the CDF of the body blockage loss (solid curves) with different choices of $d_{\text{max}}$. Also, plotted are Gaussian approximations to the loss estimated from the DKED model (dashed curves). While blockage losses increase as the blockers get close to either the transmitter or receiver, the Gaussian approximation appears to be a reasonable first-order fit across different choices of $d_{\text{max}}$.

Nevertheless, these losses are sensitive to the assumptions in the simulation methodology described in Sec. III-A. Thus, analogous to the measurements reported in Sec. III-B, link reliability studies are conducted in the third floor of the Qualcomm building, Bridgewater, NJ with the experimental prototype described in Sec. III-B to understand the impact of (human) body blockage. In these experiments, as illustrated in Fig. 4(b), the UE side of the prototype is held stationary near the vending machine(s). The UE antenna height is adjusted to 1 m with possible transmission (over an NLOS link) from one of two transmitters. One of these transmitters is at a distance of $\approx 20$ m from the UE and the other is at a distance of $\approx 40$ m. Both transmitters are held stationary and are maintained at a height of 2 m. Except for one active subarray, beam
switching across different subarrays is disabled. Uncontrolled tests are performed where people could walk by/past the UE at normal pedestrian speeds and at different distances (people could get as close as 0.5 m from the UE).

The body blockage loss corresponding to 111 RF events with humans blocking the UE are recorded and the CDF of this loss data is also presented in Fig. 5(a). The empirical mean and empirical standard deviation for the loss data are 8.54 dB and 2.45 dB, respectively. As with the self-blockage studies, the same set of four models (considered earlier) are fitted to the body blockage loss data. The parameters learned in this process as well as the KS and WKS distances between the empirical data and the fitted models are presented in Table I. From this study, we note the best fit for the data again with a Gaussian-Weibull mixture.

From Fig. 5(a), we observe that there exists a minimal yet distinct difference between the loss estimated from simulation studies and those with measurements. As mentioned earlier, these differences arise from the failure of the simulation methodology to capture real deployment scenarios and addition of more details could bridge this gap. This would be the subject of future investigations. Nevertheless, given the lack of/difficulty in obtaining measurements in outdoor scenarios, the simulation methodology described in Sec. III-A is considered for vehicular blockers with \( d_{\text{min}} = 5 \) m, \( \lambda = 4 \) and \( R = 100 \) m. From this study, Fig. 5(b) presents a comparison between human and vehicular blockers in terms of simulation studies. Typical median losses of 6.5 to 8 dB and 11.5 to 12.5 dB are seen in the human and vehicular cases, respectively. These studies illustrate the far more significant impact vehicular blockers could have in real deployments than human blockers making the understanding of such issues more important.

D. Proposed Statistical Model

Table VI summarizes the main conclusions of the studies in Sec. III-B and III-C in terms of the number, center and angular spread, and loss due to both human and vehicular blockers. While a measurements-driven loss model is proposed for human body blockage, only a simulations-based loss model (developed based on the proposed methodology in Sec. III-A) is available for vehicular blockage. A similar model is proposed by 3GPP to capture blockage effects [6, pp. 53-55]. The 3GPP model differs from the proposal in Table VI in terms of the number of blockers

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\(^{11}\) As in the self-blockage studies, RSSI could be recorded to only within a 1 dB precision.
and their blockage regions. Further, while a low-complexity statistical version of the DKED model is proposed for vehicular blockage in Table VI, a more explicit version is proposed for both body and vehicular blockage in [6]. This explicit version can lead to a substantial complexity in 5G-NR system/link level studies. Further, this explicit version critically relies on the DKED model, whose efficacy in capturing loss in the human body blockage case needs further attention as illustrated by the slight mismatch between simulation-based and measurement studies.

**TABLE VI**

**Proposed Statistical Model for Dynamic Blockage**

| Blocker index | $\phi_k$ | $x_k$ | $\theta_k$ | $y_k$ | Blockage loss (in dB) |
|---------------|----------|-------|------------|-------|-----------------------|
| $k = 2, 3, 4, 5$ (Human) | $\mathcal{U}([0^\circ, 360^\circ])$ | $2.5^\circ$ | $90^\circ$ | $15^\circ$ | Low-complexity: $\mathcal{N}(\mu = 8.5$ dB, $\sigma = 2.5$ dB) |
|               |          |       |            |       | High-complexity: Gaussian-Weibull mixture with $p_1 = 0.15$, $\mu = 9.5$, $\sigma = 1.95$, $p_2 = 0.85$, $\alpha = 9.4$, and $\beta = 3.7$ |
| $k = 6, 7, 8$ (Vehicular) | $\mathcal{U}([0^\circ, 360^\circ])$ | $15^\circ$ | $90^\circ$ | $5^\circ$ | Simulations-based: $\mathcal{N}(\mu = 12$ dB, $\sigma = 1.5$ dB) |

**IV. Time-Scales of Blockage Events**

Understanding the time-scales at which blockage events happen can help us mitigate these disruptions in terms of signal quality degradation and even possible link losses. It is important to note that these time-scales are determined by the dynamics of blockage, and in particular, the speed at which humans walk (or other blockers emerge and depart) to block a link or the speed at which the hand grabs the UE and blocks the link. Towards this goal, we define the link degradation time as the time required for the RSSI to drop from the steady-state value to its minima in the case of a good-to-moderate channel condition, or the time required for the RSSI to drop from the steady-state value to a complete link loss in the case of a poor channel condition. With this definition, the link degradation time serves as the worst-case time by which a beam switching/link adaptation procedure must be enabled to ensure that mmW coverage remains robust, reliable and seamless.

To understand the scope of link degradation and time-scales of blockage events, six experiments are performed with the experimental prototype described in Sec. [II-B](#). The prototype uses
a proprietary transmission frame structure where each sub-frame is 125 us. Analog beamforming with proprietary directional codebooks (see design principles in [16], [23]) is implemented at both the base-station and UE ends. These codebooks correspond to testing the link over 16 transmit side beams and 20 UE side beams (5 beams over four subarrays) for a beam scanning periodicity/latency of 40 ms. Thus, any link degradation/loss can be estimated to within an accuracy of ±20 ms. The first four of these six experiments correspond to link degradation due to dynamic blockage (humans walking around near the UE) and the last two experiments correspond to self-blockage (the use of the hand). Each experiment corresponds to different link/channel conditions with multiple independent tests performed in these settings. More details on these experiments including the number of tests are provided in Table [VII].

Figs. 6(a)-(b) capture the CDF of link degradation time across different channel conditions with human body blockage and self-blockage, respectively. The CDFs from the true data are presented with solid lines and piecewise linear estimated fits (across adjacent sample points) are presented with dashed lines. From these plots, we note that the link degradation time generally decreases as the channel condition deteriorates with no substantial difference between hand and body blockage dynamics. Thus these plots suggest that the time-scales at which blockages are observed at the UE end are indicative of physical movements (of either humans or the hand) which can be on the order of a few 100s of ms (or slower). Thus, from Fig. 6, it is not surprising to see that the median value of link degradation time being on the order of 200-480 ms for body blockage and 240 ms for hand blockage. Given the sub-ms latencies for beam switching possible in 5G-NR, these estimates suggest that blockage events can be handled with a robust beam management procedure.

V. SOLUTIONS TO COMBAT BLOCKAGE

Multiple solutions can either be individually/jointly considered to handle the deleterious impact of performance degradation with blockage.

- Network densification: Beamforming design for mmW systems is expected to leverage directional solution structures due to their robustness with different beamforming architectures and their implementation ease [16], [17], [36]. Thus, both the base-station and the UE are expected to steer their beams towards the dominant clusters in the channel and blockage in these directions can significantly deteriorate the performance of mmW systems.
TABLE VII

DESCRIPTION OF LINK DEGRADATION EXPERIMENTS

| Experiment | Blockage type | Channel condition | Number of tests |
|------------|---------------|-------------------|-----------------|
| 1          | Body          | Good              | 36              |
| 2          | Body          | Good-to-medium    | 32              |
| 3          | Body          | Medium            | 44              |
| 4          | Body          | Poor              | 39              |
| 5          | Hand          | Poor              | 38              |
| 6          | Hand          | Good              | 34              |

Fig. 6. CDF of link degradation time for (a) body blockage and (b) hand blockage experiments.

In this context, densifying the network with overlap in coverage across multiple cells [3] can provide higher fade margins to prevent link losses in mmW deployments. Further, the deployment of multiple base-stations could lead to the feasibility of different/distinct dominant paths from these base-stations to a certain UE via distinct reflectors, scatterers or clusters thereby reducing the risk of dramatic link degradations/failures due to blockage.

- Subarray switching: Subarray diversity is critical at the UE end due to the reduced spatial/angular coverage possible with an antenna at mmW frequencies relative to sub-6 GHz frequencies. For example, the typical angular coverage with a dipole/patch antenna is
on the order of $90^\circ$ to $120^\circ$ implying the necessity of multiple subarrays as well as a careful selection\footnote{The constraints associated with the location of camera(s), speaker, microphone, sensors, etc. lead to a careful optimization of the location of antennas in a form-factor UE design (see, e.g., Fig.~1).} of the locations of these subarrays for full spherical coverage. Thus, coverage over the sphere is realized in a form-factor UE design with distinct subarrays corresponding to distinct clusters in the channel environment. This fact can be leveraged by allowing/enabling a subarray switching procedure via beam management before an established link degrades significantly.

In this context, mmW measurements reported in [37] for indoor environments (office and shopping mall) suggest that (on average) 4-5 distinct clusters corresponding to distinct directions appear to be within a power differential of 5 dB of each other implying a reasonable level of path diversity for indoor mmW deployments. Similarly, in outdoor mobility tests with the prototype reported in [23, Sec. IV], inter-base-station beam switching and handover are shown to be both feasible and important with blockages from static geographical/topographical blockages/features, foliage, etc.

- Fall back mechanisms: With the above background, there could also be scenarios where the network is not densified sufficiently or the channel environment is sparse ensuring that there are no better clusters to switch to. In these scenarios, the UE is left with little choice but to continue to use the degraded link with some codebook enhancements (possibly proprietary from an implementation standpoint). These enhancements could help improve the array gain seen at the UE side by performing a maximum ratio combining of the effective channel corresponding to the true channel and the near-field effects of the hand. Alternately, the UE could consider fall back to legacy carriers (such as 4G/LTE) or 5G-NR carriers such as those at sub-6 GHz frequencies.

VI. CONCLUDING REMARKS

Given the prospects of accelerated deployment of 5G-NR systems, there has been an emerging interest on a number of issues that need to be addressed to make these systems technically viable and commercially profitable [28], [29]. The focus of this work is on one such aspect: blockage of mmW signals due to the user itself (hand or body parts) as well as humans or vehicles in
the vicinity of the UE. To the best of our knowledge, the impact of blockage as well as their implications in terms of PHY layer mechanisms to ameliorate their impact have not been reported for 28 or 60 GHz systems (two important use-cases of 5G-NR), especially with form-factor UE designs.

In this context, our studies at 28 and 60 GHz show that large parts of the spatial/angular coverage area can be blocked by the hand. This is because the user’s hand and body serve as primary obstacles in obscuring the radiation coverage of the UE antennas with the size of the hand being large relative to the UE. We also report measurement-driven studies of loss due to self-blockage with a 28 GHz experimental prototype. Our studies show that in contrast to prior reports of 30 to 40 dB blockage losses, even a hard hand grip with form-factor UEs could see significantly lower losses in the range of 5 to 20 dB (with a median loss of 15 dB). These discrepancies arise because of the beamwidth differences between prior studies that are based on horn antenna measurements (much smaller beamwidths) relative to form-factor phased arrays (that could have larger beamwidths). These relative beamwidth differences allow much higher signal energies to be radiated/captured in form-factor UEs. In the more optimistic scenario of looser hand grips with gap between fingers, some antenna elements can radiate/capture signal energy through the air gaps leading to even further reduced blockage losses.

We also propose a simulation methodology for capturing the impact of dynamic (human and vehicular) blockers in the vicinity of the UE. The spatial/angular coverage lost is studied and the DKED model is used to estimate the loss due to the blockers. Comparisons with measurement data of the blockage loss with human blockers in an indoor office setting shows a reasonable first-order fit with the data from the proposed simulation methodology. Given the difficulties in obtaining measurement-based estimates for loss with vehicular blockers in outdoor deployments, the proposed simulation framework could serve as a reasonable substitute for system level studies. In this context, the proposed simulation methodology as well as the statistical model generated from the data has already had some far-reaching impact on channel modeling at 3GPP. In particular, Option A of the blockage model in the 3GPP Rel. 14 channel modeling document [6, pp. 53-55] is based on ideas expounded in this paper.

Another contribution of this work is in terms of understanding the time-scales at which blockage events and their disruptions can be seen to impact the UE side. Based on experiments with the 28 GHz prototype, we show that these blockage events can be attributed to physical
movements and the time-scales at which these disruptions happen are on the order of a few 100 ms (or more). These estimates offer insights into the feasibility of mitigation mechanisms to address blockage impairments. Given a rich channel environment, network densification (as seen from the base-station perspective) or the use of multiple subarrays (as seen from the UE perspective) can help given that the 5G-NR standard allows sub-ms (or a few ms) effective latencies in beam/subarray switching. In the case of a sparse channel environment (e.g., rural settings, highways, etc.), mitigation mechanisms could be fall back on to legacy carriers or proprietary codebook enhancements (on top of the steady-state beamforming codebooks used at the UE end). The design of PHY layer enhancements to realize these ways forward could be the subject of interesting future work in this area.

**APPENDIX**

**A. Parameter Learning for a Gaussian Mixture Model**

Let \( \Phi_{\theta_1}(y) \) and \( \Phi_{\theta_2}(y) \) denote the density functions of the two Gaussians in the mixture corresponding to parameters \( \theta_i = \{\mu_i, \sigma_i\}, i = 1, 2 \). That is,

\[
\Phi_{\theta_i}(y) = \frac{1}{\sqrt{2\pi\sigma_i^2}} \cdot e^{-\frac{(y-\mu_i)^2}{2\sigma_i^2}}, \quad -\infty < y < \infty
\]

with the mixture model corresponding to a mixture probability \( p_1 \) given as

\[
\Phi_{\theta}(y) = \frac{p_1}{\sqrt{2\pi\sigma_1^2}} \cdot e^{-\frac{(y-\mu_1)^2}{2\sigma_1^2}} + \frac{(1-p_1)}{\sqrt{2\pi\sigma_2^2}} \cdot e^{-\frac{(y-\mu_2)^2}{2\sigma_2^2}}.
\]

We use \( \mathcal{L} \) to denote the log likelihood function for the data (denoted as \( y_i, i = 1, \cdots, N \)) and an unobserved latent variable, \( \Delta_i \in \{0,1\} \). The observation \( y_i \) comes from Model 1 (captured by \( \theta_1 \)) if \( \Delta_i = 0 \), or from Model 2 (captured by \( \theta_2 \)) if \( \Delta_i = 1 \). This log likelihood function is given as

\[
\mathcal{L} = \sum_{i=1}^{N} \left[ (1 - \Delta_i) \log(\Phi_{\theta_1}(y_i)) + \Delta_i \log(\Phi_{\theta_2}(y_i)) \right] + \sum_{i=1}^{N} \left[ (1 - \Delta_i) \log(1 - \pi) + \Delta_i \log(\pi) \right]
\]

where \( \pi \) denotes \( P(\Delta_i = 1) \). Since we do not know \( \Delta_i \), we replace it with its conditional expectation:

\[
\gamma_i(\theta) = \mathbb{E}[\Delta_i|\theta, \{y_j\}] = P(\Delta_i = 1|\theta, \{y_j\})
\]

and perform the Expectation Maximization algorithm for learning the parameters [38, 8.5.1, pp. 272-275 and Algorithm 8.1]. To keep this paper self-contained, we provide the parameter
learning algorithm corresponding to stopping at \( k_{\text{max}} \) iterations below. The choice of \( k_{\text{max}} \) is determined by an \emph{a priori} choice of \( \beta \) based on a stopping criterion.

**Algorithm 1** (Parameter learning for a Gaussian mixture model)

For \( k = 1 \), initialize \( \hat{p}_{1,1} = 0.5 \), \( \hat{\mu}_{1,1} = \min_i y_i \), \( \hat{\mu}_{2,1} = \max_i y_i \), \( \bar{y} = \frac{\sum_i y_i}{N} \), \( \hat{\sigma}_{1,1}^2 = \hat{\sigma}_{2,1}^2 = \frac{1}{N} \sum_i (y_i - \bar{y})^2 \).

for all \( k = 1, \ldots, k_{\text{max}} - 1 \) do

Define \( \hat{\gamma}_i = \frac{\hat{p}_{1,k}}{\sqrt{2\pi \hat{\sigma}_{1,k}^2}} \exp \left( -\frac{(y_i - \hat{\mu}_{1,k})^2}{2 \hat{\sigma}_{1,k}^2} \right) + \frac{\hat{p}_{2,k}}{\sqrt{2\pi \hat{\sigma}_{2,k}^2}} \exp \left( -\frac{(y_i - \hat{\mu}_{2,k})^2}{2 \hat{\sigma}_{2,k}^2} \right) \) for \( i = 1, \ldots, N \).

Update \( \hat{\mu}_{1,k+1} \) and \( \hat{\mu}_{2,k+1} \) with \( \frac{\sum_i \hat{\gamma}_i y_i}{\sum_i \hat{\gamma}_i} \) and \( \frac{\sum_i (1-\hat{\gamma}_i) y_i}{\sum_i (1-\hat{\gamma}_i)} \), respectively.

Update \( \hat{\sigma}_{1,k+1}^2 \) and \( \hat{\sigma}_{2,k+1}^2 \) with \( \frac{\sum_i \hat{\gamma}_i (y_i - \hat{\mu}_{1,k+1})^2}{\sum_i \hat{\gamma}_i} \) and \( \frac{\sum_i (1-\hat{\gamma}_i) (y_i - \hat{\mu}_{2,k+1})^2}{\sum_i (1-\hat{\gamma}_i)} \), respectively.

Update \( \hat{p}_{1,k+1} \) with \( \frac{\sum_i \hat{\gamma}_i}{N} \).

end for

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