Improved Propagation Modeling for Non-Terrestrial Networks

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***Abstract*—Communications systems are increasingly demanding, in terms of throughput, latency, and security requirements. To combat this, a complex system of radio access networks, each with unique and dynamic performance characteristics has evolved to support modern communications. These advancements, however, bring new and interesting challenges when tuning the network to meet the specific requirements for each supported application data flow. Here, we propose two new developments to meet this challenge. First, analytical models that can accurately estimate network performance for a wide range of radio access technologies such as 5G Terrestrial and Non-Terrestrial Networking (NTN) communications must be integrated into a single cohesive simulation environment. Second, these same models will be promoted from the simulation environment to the real world, and integrated into an advanced Software Defined Networking (SDN) controller to enable predictive network planning based on the current and estimated future state of the network. To date, the set of analytical models required to support defense network analysis has not been brought together into a single network simulation tool set, nor integrated into an SDN controller suitable for 5G terrestrial and NTN scenarios.**

***Index Terms*—Software Defined Networking, Wireless Communication, 5G, Non-terrestrial Networking, Optimization, Modeling and Simulation**

I. Introduction

Advanced communications networks and radio access technologies, such as 5G terrestrial and Non-Terrestrial Networking (NTN) communications are envisioned to enable future network applications. Some use cases like augmented reality, remote or cloud-based control, and high-definition video/sensor streaming may require increased throughput and reduced real-time latency while maintaining network security [1]. Integrating these technologies into a network scenario where human lives are at stake requires thorough vetting to ensure requirements are met, and the characteristics of each must be clearly understood to estimate the expected performance.

To understand the capabilities and expected performance of each proposed radio access technology, first analytical models describing their performance characteristics must be developed and integrated into simulation tools which can utilize these

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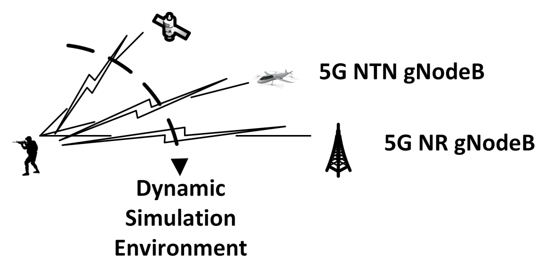

Fig. 1. Joint Domain Propagation Modeling

models to derive the full performance of the envisioned network. While there are multiple commercial and open source network simulation tools available, to date, none of these tools possess the unique set of capabilities required to fully capture the desired use case. Furthermore, standards bodies such as 3GPP, while they have specified mmWave propagation for satellite communications [2], the effects of multipath, fading, and Doppler have not yet been investigated [3], which is critical to understanding system performance of advance 5G terrestrial and NTN communications networks. While these aspects were investigated in [4], these models have not yet been integrated into the underlying ns-3 simulator, a comparative analysis versus the models presented in this research is planned for future work.

Specifically, there are two innovations we are developing in this research. First, the ability to model multiple desired 5G terrestrial and NTN waveforms as well as legacy communications technologies, along with the ability to simulate behaviour associated with simultaneous use, roaming, and switching between these technologies. Future communication devices may utilize multiple radio access technologies. Instead, they can be equipped with a variety of potential communications links, controlled by a network optimization function. By enabling smooth simulated transitions between technologies, this new paradigm of utilizing vastly different communication protocols to optimize network performance can be thoroughly vetted.

The second innovation is propagation model learning, allowing network designers to utilize field test data to update and tune the simulator's performance. No single commu-

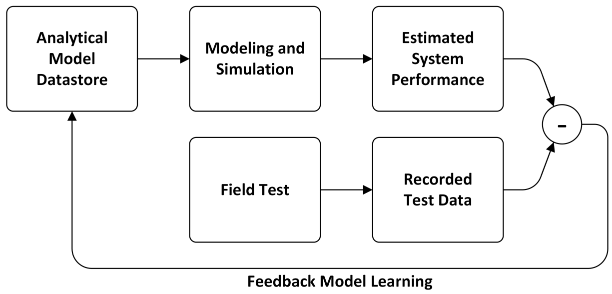

Fig. 2. Propagation Model Learning

nication model can account for every permutation of each expected scenario. In related work, machine learning and deep learning has been applied to this propagation model learning problem [5], [6]. In each of these solutions, either purely cellular based communications was considered, not the NTN based communications required for this application, or expert knowledge of the channel environment is needed to accurately predict propagation loss. In this work, we consider a more general description of the channel environment, such that the analysis can be tuned to a planned scenario, and a library of propagation models can be developed for various scenarios, enabling higher fidelity analysis for mission planning.

This modeling and simulation framework will provide accurate modeling of the current and future expected performance across a wide range of varying environmental scenarios and radio link technologies. The most immediate benefit is to enable trade analysis of potential communications technologies for planned missions or system architecture design. In future work, this technology can be applied to network optimization and control. Given a radio system with multiple radio link technologies, high fidelity system modeling of the available links could be leveraged by a predictive SDN controller to optimize the current and future planned state of the network.

II. ns-3 Capabilities and Limitations

ns-3 is an open-source network simulator that can model the full protocol stack effects of networks and end-to-end communications paths. It has well-developed models of many modern technologies, including wifi, wimax, and 4G LTE. It is also constantly evolving, with new models under development for new technologies (such as 5G) as well as new extensions to existing technologies (adding 802.11ax support to the WiFi model for example). With no licensing costs, it is an attractive platform for academic research and development for networks, and increasingly also for wireless technologies. This has led to a large worldwide support of the tool with numerous developers and maintainers from academia and industry.

However, ns-3 has some limitations as well. For one, its model library is limited. While new and emerging Commercial off the Shelf (COTS) technologies (which are under active research) are well represented, legacy communications equipment and particular NTN systems are not well represented that may still be of interest for simulations. More importantly for this project's NTN aspects, models for satellite platforms have not been developed (with the exception of the SNS3[2] add-on – which models Direct Video Broadcast (DVB) link layers, and not 5G, and models a single Geosynchronous Earth Orbit (GEO) satellite). Implementing Low Earth Orbit (LEO) constellations will require development of motion models for these satellites, along with mechanisms to determine when satellites are available to users based on position, antenna patterns, and occlusion by the earth.

Another important limitation for this project is the lack of appropriate propagation models for the intended environments: air-to-ground, air-to-air, and air-to-satellite communications at low altitudes in urban settings are very important for UAS and HAPS scenarios. This is not just a limitation for ns-3; appropriate models have not yet been defined and tested. Much attention has been paid to models for terrestrial cellular systems, which focus on users on the ground and may not be appropriate at altitudes of several thousand feet. Air-to-ground models have been developed for aviation use, but these focus on aircraft at higher altitudes and never flying in urban settings. Air-to-satellite models also exist, but again have not needed to consider an aircraft in close proximity to buildings. Dedicated propagation simulators (using ray-tracing) can be used for these scenarios, but these require large computational resources and generally will not include full-stack protocol effects.

Even with propagation models available, most simulation tools (including ns-3) require that the propagation model be explicitly configured for a simulation. That propagation model is then utilized throughout the simulation. This is undesirable for full flight evaluations: the propagation model should change as a vehicle flies from a rural to an urban setting, or from an over-water to over-land setting as appropriate. Otherwise, a user is forced to select a model that may not be appropriate for all conditions in the simulation, or perform multiple smaller simulations (one for each domain using the appropriate propagation model), and then post-process the results to stitch together a coherent view of the scenario.

While a stated goal of ns-3 is that it is ”easy to use and debug”[3] the authors believe this statement is missing an important caveat: ns-3 *might* be easy to use and debug *if the user has a degree in computer science*. All simulation tools have a learning curve; however having to build simulations at a programmatic level (using either c++ or python) likely puts the tool out of reach of most network engineers who will not have the time to learn both a programming language and the ns-3 simulation software simultaneously. Similarly, extracting data from the simulation can be difficult. While the simulator has some features for exporting packet traces and data, most often these mechanisms differ from model to model thus relying on the user to know how to properly configure the simulation to obtain the required data. In many cases, the user must write code to parse and store the data.

[2]https://www.sns3.org/content/home.php
[3]https://www.nsnam.org/about/

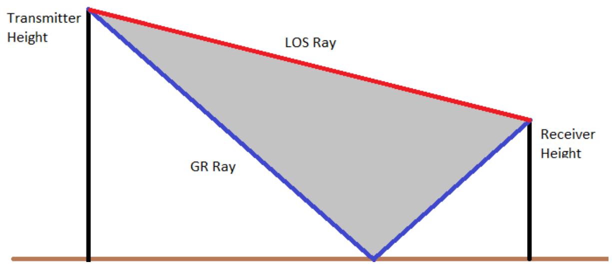

Fig. 3. Illustration of flat earth two-ray model

In order to overcome all of these limitations, the appropriate propagation models must first be developed (and tuned against measurements in the appropriate environments) and then implemented in ns-3. Additional models will also need to be developed and implemented. When necessary, existing ns-3 models will need to be modified or extended to implement features not currently supported. This includes the ability to select and switch between appropriate propagation models based on the environment surrounding each simulated vehicle. Finally, mechanisms must be developed to simplify the creation and running of simulations, and extracting useful data, so that the tool may be utilized by a wider range of users.

III. Propagation Modeling

A. Channel Model

Developing a physical layer propagation model that accurately models each use-case envisioned is the first step to understanding proposed network access layer control. As mentioned before, ns-3 uses the physical layer model proposed by the 3GPP. However, this model was developed primarily for cellular and vehicle-to-vehicle (V2V) use-cases under 4G/LTE conditions. Adjustments can be made to the existing 3GPP pathloss and channel models. This allows us to model mm-Wave scenarios in 5G NTN use cases. We first adjusted for air-to-ground (A2G).

Most, but not all, air-to-ground communication links will have a line-of-sight (LOS) component. Multipath components (sMPCs) are primarily introduced by surface obstacles but can also occur due to the aircraft itself. Under most conditions, a ground reflected (GR) ray will be the primary MPC affecting the model which allows us to generalize it as a two-ray model [7]. A flat earth model is sufficient for most scenarios. However, at distances in the tens of km, the curvature of the earth may affect the GR ray and a curved earth model would be required. But our model assumes closer distances making the flat earth model sufficient [7].

1) Path-Powers and Delays: The 3GPP model implemented in ns-3 models a set of L paths, each with delay τ_1 (s) and normalized power P_1 (W). Assuming LOS conditions, the path power of the first path is scaled to a Ricean K-Factor (KF) that describes the power difference between the LOS path and the sum power of the non-line-of-sight (NLOS) paths.

$$P_1^{[1]} = K \sum_{l=2}^{L} P_l^{[1]} \tag{1}$$

The path powers are then normalized to equal unity.

$$P_1^{[2]} = \frac{P_l^{[1]}}{\sum_{l=1}^{L} P_l^{[1]}} \tag{2}$$

Our model generalized the NLOS paths to one MPC as a GR ray. The delay, τ_{GR}, and the path power, P_{GR} of the GR ray are given by:

$$\tau_{GR} = \frac{\sqrt{(h_{BS}+h_{MT})^2 + d_{2D}^2} - \sqrt{(h_{BS}-h_{MT})^2 + d_{2D}^2}}{c} \tag{3}$$

$$P_{GR} = \frac{R^2}{2} * P_1^{[2]} \tag{4}$$

Where h_{BS} and h_{MT} are the Base Station (BS) and Mobile Terminal (MT) heights, respectively. d_{2D} is the 2-dimensional distance between the BS and MT and c is the travel speed of the ray or the speed of light. R represents the reflection coefficient which is discussed in a later section of this paper.

To obtain the correct delay and angle spreads, P_{LOS} must be adjusted with Equation 2 to keep the normalization of path powers.

$$P_{LOS} = \left(1 - \frac{R^2}{2}\right) * P_1^{[2]} \tag{5}$$

2) Angles of Arrival and Departure: The next step is to include the angles of arrival and departure for the GR ray. The four angles used are the azimuth angles of arrival (AoA) and departure (AoD) and the elevation angles of arrival (EoA) and departure (EoD). The azimuth angles for both the LOS and GR ray are the same. So, we only need to consider the elevation angles.

The 3GPP model maps the path powers to a wrapped Gaussian distribution to calculate the angles for the NLOS paths [8]. The strongest path gets normalized to $\theta = 0$ with unit power. All other paths get relative angles depending on their path power.

$$\theta_l^{[1]} = \frac{\sigma_\theta}{C_\theta(L,K)} * \sqrt{-ln\left(\frac{P_l}{\max(P_l)}\right)}, \tag{6}$$

where σ_θ is the predetermined angular spread (AS) in radians and $C_\theta(L,K)$ is a correctional term that considers the KF and the mapping of discrete paths to a continuous distribution.

Two new random variables are introduced which add random variation to the angles. $X_l \sim \{-1, 1\}$ is the sign of the angle and $Y_l \sim N(0, (\sigma_\theta^2/7^2))$ adds a random variation to the angle.

$$\theta_l^{[2]} = X_t * \theta_l^{[1]} + Y_l \tag{7}$$

The positions of the BS and MT are deterministic which means that their LOS/NLOS angles are also deterministic. These angles are used to adjust $\theta_l^{[2]}$ to incorporate position.

$$\theta_{LOS}^{a} = \arctan\left(\frac{h_{BS} - h_{MT}}{d_{2D}}\right) \tag{8}$$

$$\theta_{LOS}^{d} = -\theta_{LOS}^{a} \tag{9}$$

$$\theta_{GR}^{a} = -\theta_{GR}^{d} = \arctan\left(\frac{h_{BS} + h_{MT}}{d_{2D}}\right) \tag{10}$$

$$\theta_l^{[3]} = \theta_l^{[2]} - \theta_1^{[2]} + \theta_{LOS}^{d/a} \tag{11}$$

3) Polarization: The antenna polarization is described using spherical coordinates, aligning the electric field with the 3 spherical unit vectors $\hat{e}_\theta$, $\hat{e}_\phi$, and $\hat{e}_r$ [8] [9]. The far-field of the antenna has no electric field component in the propagation direction, r. Therefore, the antenna radiation pattern is comprised of components in the $\hat{e}_\theta$ direction and the $\hat{e}_\phi$ direction. This is represented as a 2-element vector.

$$F(\theta, \phi) = \left(F^{[\phi]}(\theta, \phi), F^{[\theta]}(\theta, \phi)\right) \tag{12}$$

The path between the transmitter and receiver is represented by:

$$g = \sqrt{P} * \left(F_r(\theta^a, \phi^a)^T\right) * M * \left(F_t(\theta^d, \phi^d) * e^{-j\frac{2\pi d}{\lambda}}\right) \tag{13}$$

F_r and F_t are the receiver and transmitter polarimetric antenna responses, respectively. λ is the wavelength, d is the path length, and (θ^a, ϕ^a) and (θ^d, ϕ^d) are the arrival and departure angles, respectively.

M is the $2x2$ polarization coupling matrix. Normalization is removed and the matrix is interpreted as a reflection operation that transforms the outgoing transmitter path to the incoming receiver path. M can be calculated with the following equations:

$$M_{LOS} = \left(1 - \frac{R^2}{2}\right)^{-\left(\frac{1}{2}\right)} * e^{j\psi_{LOS}} * \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \tag{14}$$

$$M_{GR} = \frac{\sqrt{2}}{R} * e^{j\psi_{GR}} * \begin{bmatrix} R_\parallel & 0 \\ 0 & R_\perp \end{bmatrix} \tag{15}$$

The phase of each term is represented by ψ. The LOS and GR phases are given by the following equations:

$$\psi_{LOS} = \frac{2\Pi}{\lambda} * \sqrt{(h_{BS} - h_{MT})^2 + d_{2D}^2} \tag{16}$$

$$\psi_{GR} = \frac{2\Pi}{\lambda} * \sqrt{(h_{BS} + h_{MT})^2 + d_{2D}^2} \tag{17}$$

4) Reflection Coefficient: The reflection coefficient is a function of the electromagnetic properties of the material. ϵ is the complex-valued relative permittivity, ϵ_r is the relative permittivity of the material, ϵ_0 is the permittivity of free space, and σ is the conductivity of the material. The reflection coefficients are then calculated using the following equations [8]:

$$\epsilon = \epsilon_r - j\frac{\sigma}{2\Pi * f_c * \epsilon_0} \tag{18}$$

$$R_\perp = \frac{\sin(\theta^r) - Z}{\sin(\theta_r) + Z}; R_\parallel = \frac{\epsilon * \sin(\theta^r) - Z}{\epsilon * \sin(\theta^r) + Z} \tag{19}$$

$$Z = \sqrt{\epsilon - (\cos(\theta^r))^2} \tag{20}$$

$$R = \sqrt{0.5 * |R_\parallel|^2 + 0.5 * |R_\perp|^2} \tag{21}$$

$$\theta^r = -\theta_{GR}^{d} = \arctan\left(\frac{h_{BS} + h_{MT}}{d_{2D}}\right) \tag{22}$$

B. Pathloss and Fading

1) Pathloss: The 3GPP model uses a dual-slope pathloss model for urban microcell (UMi) LOS scenarios. This means that the PL is a function of distance to the 4th power. The model incorporates a break-point distance (BP) that determines the PL equation to use. At distances lower than the BP, the PL is similar to Frii's free-space model. At distances larger than the BP, a second slope accounts for the influence of the GR ray [8] [9].

$$d_{BP} = 4 * (h_{BS} - 1) * (h_{MT} - 1) * \frac{f_c}{c} \tag{23}$$

$$PL_1 = 21\log_{10}(d_{3D}) + 32.4 + 20\log_{10}\left(f_c^{GHz}\right) \tag{24}$$

$$PL_2 = 40\log_{10}(d_{3D}) + 32.4 + 20\log_{10}\left(f_c^{GHz}\right) - 9.5\log_{10}\left(d_{BP}^2 + (h_{BS} - h_{MT})^2\right) \tag{25}$$

However, at larger distances, the PL is a combination of (24) and the two-ray PL. This makes the resulting PL a function of distance to the 6th power. To compensate for this, our model adds a third slope and second BP to the 3GPP model.

$$d_{BP2} = 41.7 * h_{BS} * h_{MT} * f_c^{GHz} \tag{26}$$

$$PL_3 = 20\log_{10}(d_{3D}) + 32.4 + 20\log_{10}\left(f_c^{GHz}\right) - 9.5\log_{10}\left(d_{BP}^2 + (h_{BS} - h_{MT})^2\right) + 10\log_{10}\left(d_{BP2}^2 + (h_{BS} - h_{MT})^2\right) \tag{27}$$

2) Shadowing: To model slow-fading or shadowing effect, a log-normal scale around the mean PL with a Gaussian distribution and 0 mean and standard deviation is used [9]. Adjacent values are correlated due to the slow-fading process compared to the distance change between values. The normalized autocorrelation function can be expressed as:

$$R(\Delta x) = e^{-\frac{|\Delta x|}{d_{corr}}} \quad (28)$$

With d_{corr} being the correlation distance, which is dependent on the environment. The 3GPP shadowing model uses parameters specific to V2V communication. To get accurate results for our model, the parameters need to be updated for A2G communication.

3) Fast-Fading: Small-scale fading or fast-fading is a propagation characteristic that arises due to reflectors and scatterers in the environment. The 3GPP model accomplishes this through the channel model by stochastically generating paths produced by environmental scatterers. However, our model condenses the channel model into two dominating components, the LOS and GR ray. The Nakagami-m model is a fading distribution which is sufficient for A2G communication links [10].

The Nakagami-m model has a fading shape parameter, m, which is expressed as:

$$m = \frac{\left(E[R^2]\right)^2}{Var[R^2]} \quad (29)$$

Where R is the amplitude of the received signal. Parameter m can be empirically estimated for $m \geq 1/2$. Our model uses two values for m determined by the channel condition: m_L is used in LOS scenarios and m_N is used in NLOS scenarios. Parameters can be found in Table I.

IV. Results

The deterministic fluctuation pattern caused by the GR ray can be seen in Figure 4. The orange line is the current ns-3 implementation of the 2-ray model. The blue line is our proposed 2-ray model. The fluctuating pattern is created as the phase of the GR ray rotates as the distance changes. Both lines also follow the same average, which is expected as the fluctuations occur around the LOS ray's power.

As seen in Figure 4, the 3GPP model creates a smooth, exponentially decreasing curve. This curve fails to model the interference of the GR ray on the LOS ray. Our model also follows this exponential curve. The interference of the rays can be seen in the form of distinct fluctuations around the 3GPP (average) curve. This shows that our model successfully models the interference in the propagation model.

Additionally, we still need to test the channel and fading models. To do this, we set up a simple A2G scenario using our custom model in tandem with the 5G LENA NR module. This environment consists of one stationary receiver at the origin and one moving transmitter of altitude 100m, flying from $x = -2000$ to $x = 2000$. There is a building behind the receiver blocking the LOS path after the transmitter flies overhead and enters the positive x axis. The blue line is the current 3GPP implementation while the orange line is our custom model. The parameters used can be seen in Table I and the results of this example are seen in Figure 5.

Here, we observe the effects of the channel model. The LOS

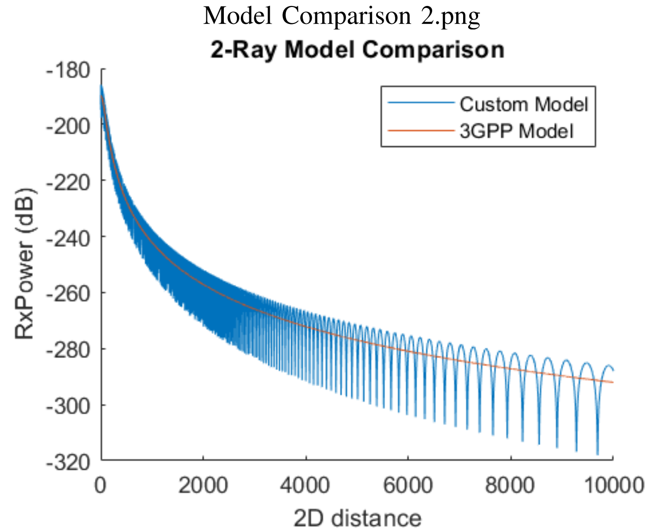

Fig. 4. ns-3 2-ray model vs. Custom 2-ray model.

TABLE I
PARAMETERS FOR 5G SIMULATION.

Parameter	Value
F_c	28GHz
σ_{LOS}	5.3dB
σ_{NLOS}	5.27dB
d_{corr}-LOS	10m
d_{corr}-NLOS	13m
m_L	3
m_N	2

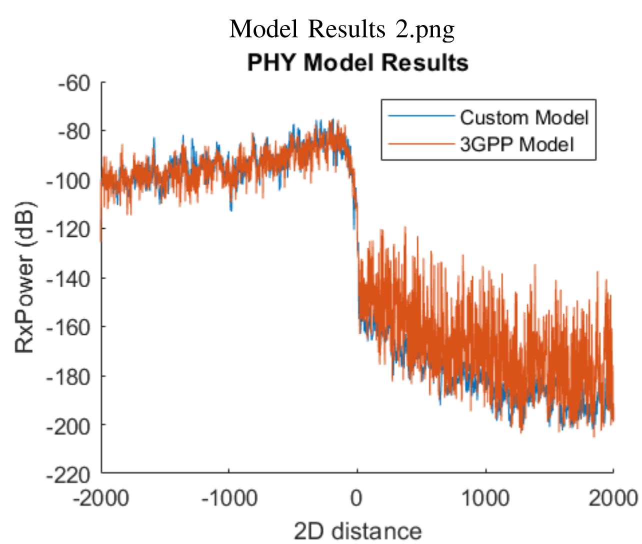

Fig. 5. 3GPP vs Custom Model Results

condition is observed while the 2D distance is negative and NLOS condition is observed while the 2D distance is positive. Under LOS conditions, the output of the models follow the same average which is similar to the propagation example from Figure 4. The effect of the fluctuations is observed through the spikes and dips in the custom model's output compared to the 3GPP model. We see a drop in both models as the 2D distance between nodes approaches 0. Here, the building in the scenario is blocking the LOS channel, causing the models to switch to NLOS conditions. The custom model fluctuates less than the 3GPP under these conditions. It also has a lower average output. This is due to the lack of scatterers in our 2-ray channel model. The LOS and GR rays propagate through the building and experience a higher building loss with less variation.

These results demonstrate that new propagation models can be developed following the architecture of the existing 3GPP models in ns-3. Since the 5G NR models were created using the 3GPP propagation model framework, these new models can be easily integrated into the 5G codebase.

A. Future Work

Currently, our model only supports single use-case environments (e.g. terrestrial or NTN). In a real communication environment, the system will need to switch between the different cases as the environment evolves over time. This requires the implementation of a dynamic propagation model that allows the system to switch between propagation models to support the current use-case. Our model also does not take Doppler into consideration and will need to be implemented. Another step towards creating an efficient propagation model is tuning our simulated model with test data. This allows us to find deficiencies within the model and remove them before moving on to a physical test environment. Although more research is needed for a fully developed propagation model, our work provides a foundation to build an accurate and reliable simulation for 5G NR communication. NTN propagation models have been investigated by 3GPP [4]. Integrating these models into ns-3 and a detailed comparison to the proposed approach is planned future work.

V. Towards Network Optimization

Developing a simulation tool capable of predicting the performance of both 5G terrestrial and NTN network is vital to characterizing expected network performance, but it is only the first step towards a network optimization algorithm. This research is rapidly leading to this goal, where the ability to predict network performance can be integrated into an advanced and predictive SDN network optimization algorithm.

In modern communication systems, there can be multiple radio access networks available, each with varying network performance characteristics. By using the algorithms developed in this research, it will be possible to estimate the current and future expected performance of each potential network path, whether that path utilizes terrestrial communication or through aerial NTN relay or satellite connectivity. Each network can be characterized, each potential network use case can lead to additional tuned system models, and through machine learning, a network optimization algorithm can generate a network plan that best meets the unique needs of each defense mission.

VI. Acknowledgment of Support and Disclaimer

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References

[1] James F. "Frank" Hudson Jr. Mission assurance in joint all-domain command and control. *Air and Space Power Journal*, 2021.
[2] 3GPP. Solutions for nr to support non-terrestrial networks (ntn). *TR 38.821 (Release 16)*, 2020.
[3] Marco Giordani and Michele Zorzi. Non-terrestrial networks in the 6g era: Challenges and opportunities. *IEEE Network*, 35(2):244–251, 2020.
[4] 3GPP. Study on new radio (nr) to support non-terrestrial networks. *TR 38.811 (Release 15)*, 2020.
[5] Faris A. Almalki and Marios C. Angelides. A machine learning approach to evolving an optimal propagation model for last mile connectivity using low altitude platforms. *Computer Communications*, 142-143:9–33, 2019.
[6] Usama Masood, Hasan Farooq, and Ali Imran. A machine learning based 3d propagation model for intelligent future cellular networks. In *2019 IEEE Global Communications Conference (GLOBECOM)*, pages 1–6, 2019.
[7] David W Matolak and Ruoyu Sun. Unmanned aircraft systems: Air-ground channel characterization for future applications. *IEEE Vehicular Technology Magazine*, 10(2):79–85, 2015.
[8] Stephan Jaeckel, Leszek Raschkowski, Shangbin Wu, Lars Thiele, and Wilhelm Keusgen. An explicit ground reflection model for mm-wave channels. In *2017 IEEE Wireless Communications and Networking Conference Workshops (WCNCW)*, pages 1–5. IEEE, 2017.
[9] ETSI 3GPP. Lte; 5g; study on channel model for frequencies from 0.5 to 100 ghz. Technical report, 3GPP, 2017.
[10] Long Zhang, Hui Zhao, Shuai Hou, Zhen Zhao, Haitao Xu, Xiaobo Wu, Qiwu Wu, and Ronghui Zhang. A survey on 5g millimeter wave communications for uav-assisted wireless networks. *IEEE Access*, 7:117460–117504, 2019.