Explainable AI with SHAP Sensitivity Analysis for Data Driven Propagation Modeling of 5G and Beyond Networks

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Abstract

As 5G and 6G technologies increase wireless network complexity, traditional propagation models, based on empirical or semi-empirical formulas, often fail to capture the intricate interactions between radio waves and their environments, crucial for effective network planning and management. Data-driven models using machine learning and large datasets offer superior accuracy in predicting signal propagation. However, as these models grow in complexity, understanding their decision-making processes becomes vital. SHAP (SHapley Additive exPlanations) analysis provides valuable insights into these models, illustrating feature contributions through tools like waterfall plots. This enhances transparency and trust, crucial for effective network planning and management in advanced wireless communication systems. This report focuses on the Shap analysis of data driven propagation modeling data set for a dense urban environment.

1 Introduction

1.1 Background and Motivation for Data-Driven Propagation Models

The rapid evolution of 5G technology and the forthcoming deployment of 6G networks have dramatically increased the complexity of wireless communications. These advancements demand more precise and efficient propagation models to accurately predict radio wave behavior [1]. Traditional empirical and semi-empirical models, although useful, often struggle to capture the dynamic and complex nature of modern propagation environments, particularly in dense urban areas. These conventional models rely heavily on site-specific measurements and static formulas, which limit their adaptability and precision [2].

Deterministic models, such as those based on ray tracing, simulate the physical interactions of radio waves with their environment, providing higher accuracy. However, these models are computationally demanding and time-consuming, making them less suitable for real-time applications and large-scale network optimization [3]. This challenge is where data-driven propagation models show their strengths. By leveraging machine learning (ML) algorithms and extensive datasets, these models can learn intricate propagation patterns directly from the data, combining accuracy with efficiency to outperform traditional methods [4]. The data-driven approach adopted in this study excels in handling the multifaceted nature of propagation environments. By integrating diverse features, including base station (BS) configurations, user equipment (UE) parameters, and environmental characteristics, these models deliver highly accurate predictions of path loss and received signal strength (RSS) [4]. Such precise modeling is crucial for network planning, optimization, and management, facilitating more reliable and efficient communication networks [5].

1.2 Motivation for Explainable AI in Propagation Modeling

As data-driven models become increasingly complex, understanding their decision-making processes becomes very important, especially in critical applications where transparency and trust are essential. Explainable AI (XAI) techniques address this need by making the inner workings of machine learning models interpretable to humans. SHAP (SHapley Additive exPlanations) analysis stands out in this regard, providing a robust framework for interpreting model outputs [6, 7]. The Shapley value is a concept from cooperative game theory that determines the fair distribution of payouts (in this case, feature contributions) among players (features) by considering all possible combinations of players. SHAP values fairly attribute the contribution of each feature to the model's predictions, offering detailed insights into the decision-making process [8]. In propagation modeling, SHAP analysis helps explain how different features influence signal propagation predictions. By enhancing the transparency of machine learning models, SHAP analysis ensures that decisions made by these models can be trusted and effectively utilized for network optimization. However, before delving into the details of the SHAP analysis and its implementation for the propagation modeling dataset, we explain the details of this dataset in the following subsection.

1.3 Description of Propagation Modeling Dataset

The dataset used in this analysis consists of about 30K instances, each representing a unique combination of environmental and configuration parameters affecting the propagation of radio signals. The target variable is reference signal received

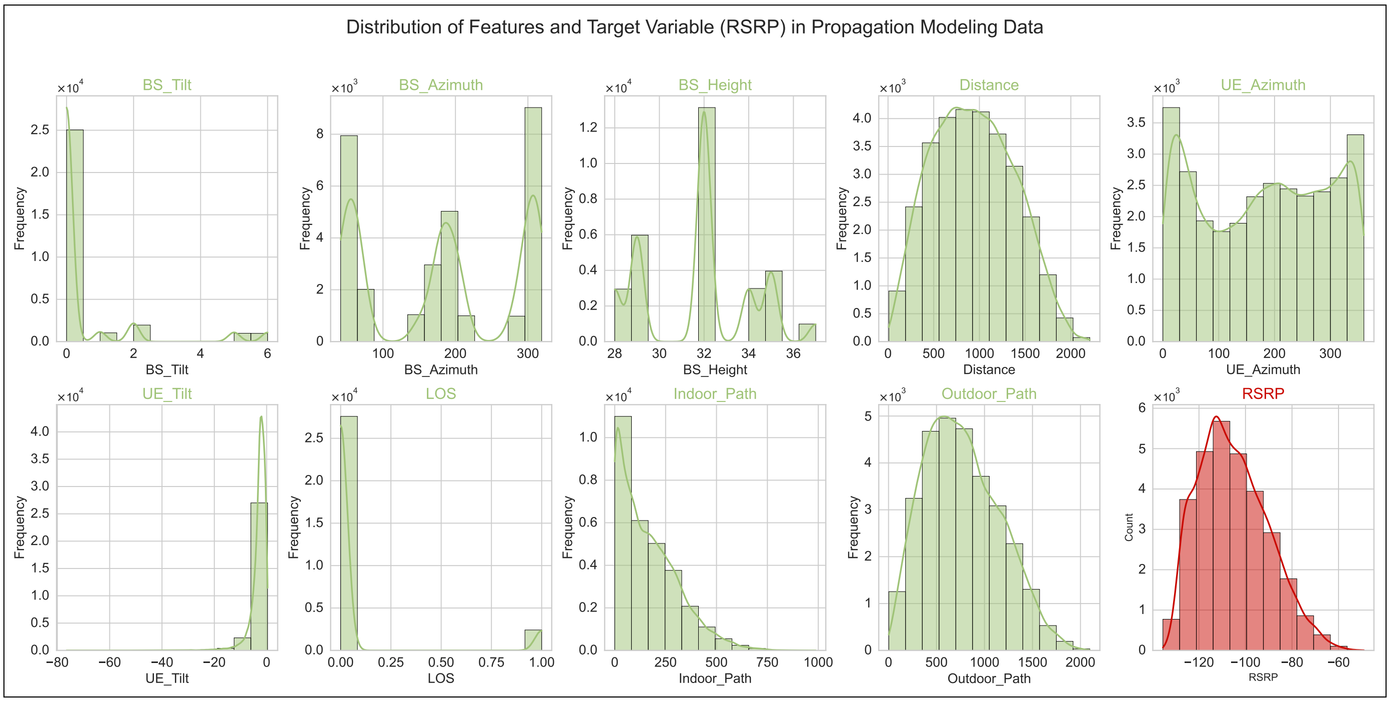


Figure 1: Distribution of 9 Features and 1 Target Variable (RSRP) in Propagation Modeling Data.

power (RSRP), which is a critical indicator of signal strength received by user equipment. The dataset is generated by simulating the realistic 5G network in a state of the art planning tool, Atoll, widely used in telecom industry, to model the propagation of signals through environments with realistic geographic clutter. More details about the simulation setup and feature engineering are skipped for brevity, and are given in recent works from our research group in [3]. Below is a detailed description of the features included in the dataset, and distribution of each feature and target variable is depicted in Figure 1:

1. **BS_Tilt (int):** This feature denotes the tilt angle of the base station antenna. The tilt angle is crucial for controlling the vertical radiation pattern of the antenna, impacting coverage and interference. Adjusting the tilt can significantly influence the received signal strength by directing the signal more accurately towards the intended coverage area. The distribution of BS_Tilt is heavily skewed towards zero, indicating that most base stations have minimal tilt. A few instances have higher tilt angles.
2. **BS_Azimuth (float):** The azimuth angle of the base station antenna, measured in degrees, specifies the horizontal direction of the antenna's radiation pattern. Proper alignment of the azimuth angle ensures optimal coverage and reduces interference with adjacent cells. BS_Azimuth values are clustered around specific angles, suggesting preferred orientations for the antennas.
3. **BS_Height (int):** This feature represents the height of the base station antenna above ground level. The height can affect signal propagation characteristics, such as path loss and line-of-sight conditions, thereby influencing the received signal strength. The distribution shows distinct peaks, indicating common typical installation heights for base station antennas being practiced in industry.
4. **Distance (float):** This is the distance between the base station and the user equipment, measured in meters. Distance is a fundamental factor in propagation modeling, as signal strength typically decreases with increasing distance due to path loss. The Distance feature has a broad distribution, with a noticeable decrease in frequency at greater distances, reflecting typical cellular network coverage patterns.
5. **UE_Azimuth (float):** The azimuth angle of the user equipment, indicating the direction it is facing. The orientation of the UE can affect the received signal strength, particularly in scenarios where the signal is directional. The distribution of UE_Azimuth is relatively uniform, suggesting varied orientation in all directions of user equipment in the dataset.
6. **UE_Tilt (float):** This feature denotes the tilt angle of the user equipment. The tilt angle can impact the quality of the received signal, especially if the UE is positioned at an angle relative to the incoming signal. The UE_Tilt feature is highly skewed, with most values near zero, indicating minimal tilt for most user equipment.
7. **LOS (int):** A binary indicator of whether there is a line-of-sight (LOS) condition between the base station and the user equipment. LOS conditions generally result in stronger received signals due to the absence of obstructions. The LOS feature is binary, with the histogram showing a higher frequency of non-LOS conditions.
8. **Indoor_Path (float):** The length of the path that the signal travels indoors, measured in meters. Indoor environments introduce significant signal attenuation due to walls and other obstacles, affecting the received signal strength. The Indoor_Path feature is heavily skewed towards shorter distances, indicating that most indoor paths are relatively short.

9. **Outdoor_Path (float):** The length of the path that the signal travels outdoors, measured in meters. Outdoor propagation is typically less obstructed than indoor propagation, but it can still be influenced by various environmental factors. The Outdoor_Path feature shows a broad distribution with many instances at moderate distances.

10. **RSRP (float):** The target variable indicating the signal strength received by user equipment. RSRP is crucial for evaluating the quality of service in a cellular network. The RSRP values form a bell-shaped distribution, indicating a normal distribution of received signal strength across the dataset.

2 Explain AI using SHAP Analysis

2.1 SHAP Analysis: Theoretical Background

As AI systems become increasingly integrated into critical applications, the need for transparency and interpretability in these systems has grown significantly. XAI aims to make the inner workings of AI models understandable to humans, ensuring that decisions made by these models can be trusted and validated. One powerful tool in the XAI toolkit is SHAP analysis as briefly described in the introduction. SHAP analysis provides a unified framework for interpreting the output of machine learning models. It is based on Shapley values from cooperative game theory, which fairly distributes the payout (in this case, the model's prediction) among the features based on their contribution. By attributing importance scores to each feature, SHAP helps identify how each input feature impacts the model's predictions, offering insights into the decision-making process of complex models. This interpretability is crucial for validating models, diagnosing issues, ensuring fairness, and building trust in AI systems.

The Shapley value for a feature i is defined as the average marginal contribution of the feature across all possible coalitions (subsets) of features. The mathematical formulation is as follows:

$$\phi_i = \sum_{S \subseteq N \setminus i} \frac{|S|!, (|N| - |S| - 1)!}{|N|!} [f(S \cup i) - f(S)] \tag{1}$$

- ϕ_i is the Shapley value for feature i.
- N is the set of all features.
- S is a subset of features not including i.
- $f(S)$ is the model prediction using the features in subset S.
- $f(S \cup \{i\})$ is the model prediction using the features in subset S plus feature i.

In this formulation:

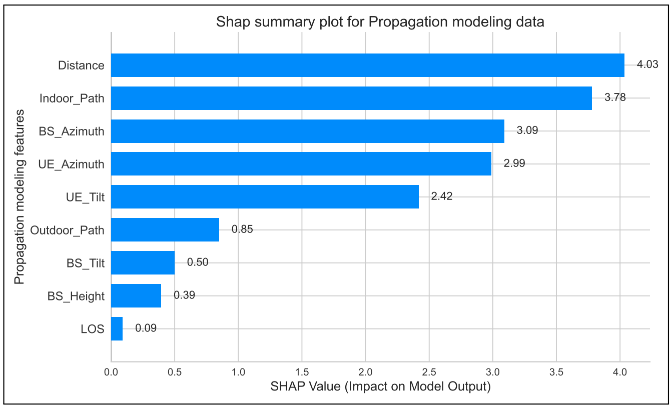
- $|S|$ represents the number of elements in subset S.
- The term $\frac{|S|!\,(|N|-|S|-1)!}{|N|!}$ is a weighting factor that accounts for the different possible permutations of feature sets.

The Shapley values satisfy several desirable properties:

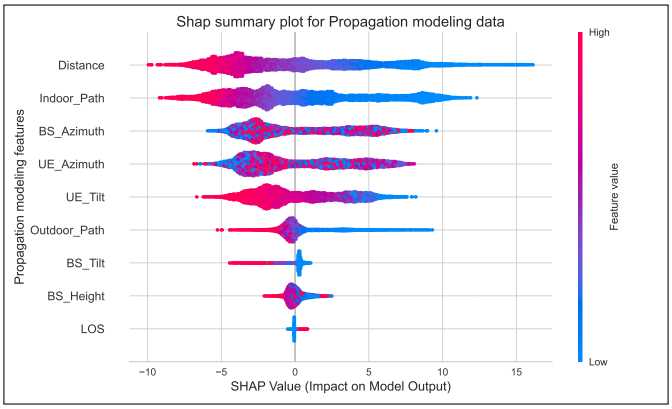
- **Efficiency**: The sum of the Shapley values for all features equals the total prediction.
- **Symmetry**: If two features contribute equally to all coalitions, they receive the same Shapley value.
- **Dummy**: If a feature does not contribute to any coalition, its Shapley value is zero.
- **Additivity**: For any two models, the Shapley values of their sum is the sum of their Shapley values.

SHAP analysis stands out as a highly suitable tool for Explainable AI due to its strong theoretical foundation, versatility, and comprehensive interpretability features. Grounded in cooperative game theory, SHAP leverages Shapley values to fairly attribute the contribution of each feature to a model's prediction, ensuring rigorous and mathematically sound explanations. Its model-agnostic nature allows SHAP to be applied across various types of machine learning models, from linear regressions to complex neural networks and ensemble methods. SHAP values adhere to principles of consistency and local accuracy, providing reliable and precise explanations. Furthermore, SHAP supports both global and local interpretability, offering insights into overall feature importance and individual predictions. The intuitive visualizations provided by SHAP, such as summary plots, dependence plots, and force plots, facilitate clear communication of model behaviors to stakeholders. Additionally, SHAP can identify feature interactions, uncovering complex relationships within the data. These attributes make SHAP an indispensable tool for achieving transparency, diagnosing model behaviors, ensuring fairness, and building trust in AI systems. In the following delver into the visual depiction of global and local interpretability plots for the dataset under consideration.

In our implementation of SHAP analysis, we have used the list of models, mostly tree based such as the Catboost, XGBoost, LightGBM etc., from PyCaret library, and choose the best performing model for the analysis. However, the implementation is flexible to different models, but SHAP analysis is model agnostic, so choice of that does not affect the analysis in any significant manner.



(a) Bar plot showing the ranking and relative influence of features on the model's predicted RSRP.



(b) Beeswarm plot, providing overview of how the variables impact the model's predictions across all of the data.

Figure 2: First global interpretability parameter, *SHAP summary*, highlighting the impact of various features, measured as SHAP values, and ordered by decreasing importance, on predicting the propagation modeling target variable, RSRP.

2.2 Global Interpretability: Predictions across the entire dataset

The global interpretation methods explain the general behavior of a machine learning model in relation to the entire distribution of its input variables. SHAP accomplishes this by aggregating the SHAP values of individual instances across the entire dataset, providing a comprehensive understanding of each feature influences on model predictions on a global scale.

2.2.1 SHAP summary plots

The SHAP summary plots offer a comprehensive understanding of feature importance and their impacts on the model's predictions in the context of data-driven propagation modeling. These plots depict the contributions of various features to the RSRP, i.e., target variable in propagation modeling data as shown in Figure 2.

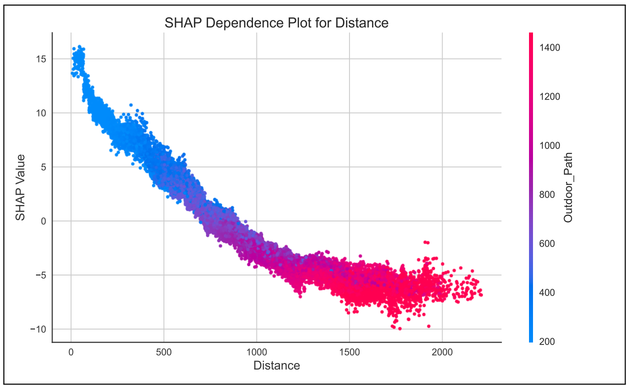
Bar plot The starting point for global interpretation is a SHAP bar graph, which ranks the characteristics by their average absolute SHAP values, reflecting their general importance to the model as shown in Figure 2a. In this plot, Distance emerges as the most influential feature, followed closely by Indoor_Path, BS_Azimuth, UE_Azimuth, and UE_Tilt, while the outdoor path comes later, highlighting the data is mostly taken in dense urbane environment. This ranking indicates that these features have the most substantial impact on the model's predictions. For instance, Distance significantly affects RSRP, which aligns with the fundamental principle that signal strength generally decreases with increasing distance from the source. Similarly, Indoor_Path highlights the importance of indoor environments, which typically introduce significant signal attenuation due to obstacles like walls. The azimuth and tilt angles of both the base station (BS) and user equipment (UE) also play crucial roles, reflecting how directional orientation and positioning influence signal reception.

Beeswarm plot The second plot in this category is a SHAP beeswarm depicted in Figure 2b, which provides a more detailed view by showing the distribution of SHAP values for each feature across all instances. In this and all subsequent scatter plots, each point represents a data instance, colored by the feature value from low (blue) to high (red). This plot not only confirms the ranking of feature importance but also reveals the direction and magnitude of each feature's effect on the prediction. In the beeswarm plot, Distance consistently shows negative SHAP values, indicating that greater distances generally reduce RSRP. Conversely, Indoor_Path displays a mix of positive and negative SHAP values, suggesting complex interactions where the impact on RSRP can vary depending on specific conditions. The azimuth and tilt angles (BS_Azimuth, UE_Azimuth, UE_Tilt) exhibit a broad spread of SHAP values, reflecting their intricate influence on signal strength, mainly because of varying environmental contexts and equipment orientations. The beeswarm plot also highlights the significance of Outdoor_Path, BS_Height, and BS_Tilt, although their impacts are less pronounced compared to the top-ranked features. LOS (line-of-sight) shows minimal influence, which may indicate that the dataset predominantly contains non-LOS scenarios and that LOS conditions do not vary significantly across instances.

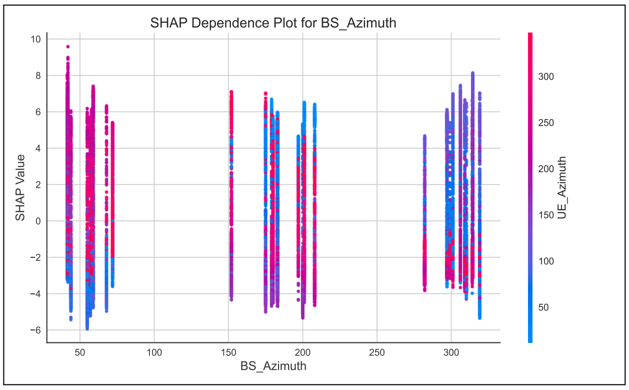
2.2.2 SHAP dependence plots

Beeswarm plots offer a dense and comprehensive overview of SHAP values for numerous features simultaneously, providing a broad understanding of feature importance and impact. However, to delve deeper into the relationship between a specific feature's values and the model's predicted outcomes, SHAP dependence plots are essential. These plots, shown in Figure 3, not only show the direct effect of each feature, but also highlight the interaction effects with other features, providing a more nuanced understanding of the model's behavior. In the context of data-driven propagation modeling, SHAP dependence plots help us to understand how key features such as distance, Indoor_Path length, and azimuth angles affect the predicted RSRP. Although, there can be many different dependence plots, based on the possible combinations of

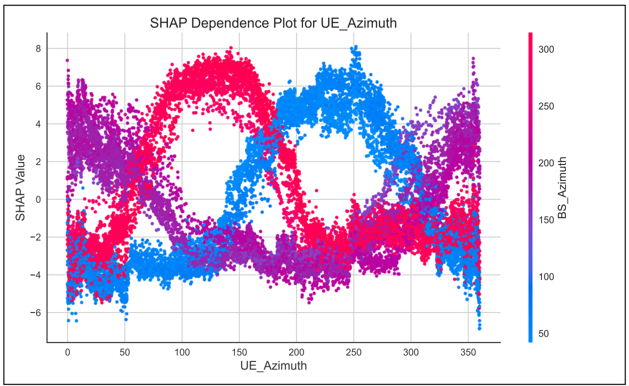
(a) SHAP dependence plot to highlight the interactions between *Distance* and *Outdoor_Path* features.



(b) SHAP dependence plot to highlight the interactions between *BS_Azimuth* and *UE_Azimuth* features.



(c) SHAP dependence plot to highlight the interactions between *UE_Azimuth* and *BS_Azimuth* features.



(d) SHAP dependence plot to highlight the interactions between *UE_Tilt* and *BS_Azimuth* features.

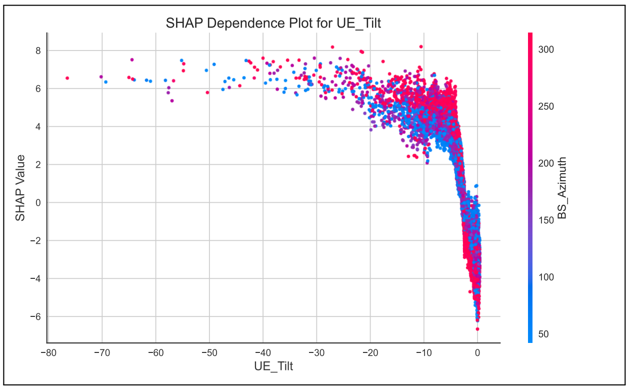


Figure 3: The *SHAP dependence* plot to highlight interaction between a certain feature (x-axis), and the most interacting feature (with value highlighted by the color intensity shown in the vertical bar on the right side of each figure) with it.

any two features from the available 9 features, we have shortlisted only 4 of them in Figure 3 to depict various possible interaction patterns.

SHAP Dependence Plot for Distance The SHAP dependence plot depicted in Figure 3a provides an insightful analysis of the interaction between the Distance feature and the most interacting feature with it, i.e., Outdoor Path', highlighting their impact on the model's predictions. This plot shows the relationship between the values of the Distance feature and its corresponding SHAP values, which represent the contribution of Distance to the model's prediction. As Distance increases, the SHAP value generally decreases, indicating a negative relationship between Distance and the model's output. Specifically, when the Distance value is low, the SHAP value is high, suggesting that shorter distances positively influence the prediction. Conversely, as the Distance value increases, the SHAP value becomes more negative, indicating that longer distances negatively impact the prediction. The color gradient in the plot represents the values of the Outdoor Path feature, illustrating how it interacts with the Distance feature. When the Outdoor Path values are low (represented by blue points), the negative impact of Distance on the SHAP value is less pronounced. However, as the Outdoor Path values increase (shifting towards red points), the negative impact of Distance on the SHAP value becomes more significant. This interaction effect suggests that the presence of outdoor paths exacerbates the negative influence of distance on the model's prediction, which makes the intuitive sense with signal propagation.

SHAP Dependence Plot for BS_Azimuth Similar to the previous case, the SHAP dependence plot for BS_Azimuth in Figure 3b demonstrates the relationship between the this feature, SHAP values depicted on y-axis, and highest interacting feature, UE_Azimuth depicted by the color. The plot shows that the BS_Azimuth values are discrete, with three different clusters, and the SHAP values for BS_Azimuth are widely dispersed, without any particular relation/trends between BS_Azimuth and UE_Azimuth angles. This is intuitive correct because from a given reference, UE relative position to the BS antenna boresight matters the most for the RSRP, and since we are having 3-sectored BS antennas, hence, the UE is locked to the best antenna with highest coverage.

SHAP Dependence Plot for UE_Azimuth The previous analysis is further explored from a different perspective in Figure 3c, where the SHAP dependence plot for UE_Azimuth highlights the interaction with BS_Azimuth. The SHAP values for UE_Azimuth show significant variation across its range, with distinct patterns emerging based on the values of BS_Azimuth'. The plot reveals that certain values of UE_Azimuth lead to higher positive SHAP values when paired

(a) SHAP waterfall plot for data instance = 1. (b) SHAP waterfall plot for data instance = 9.

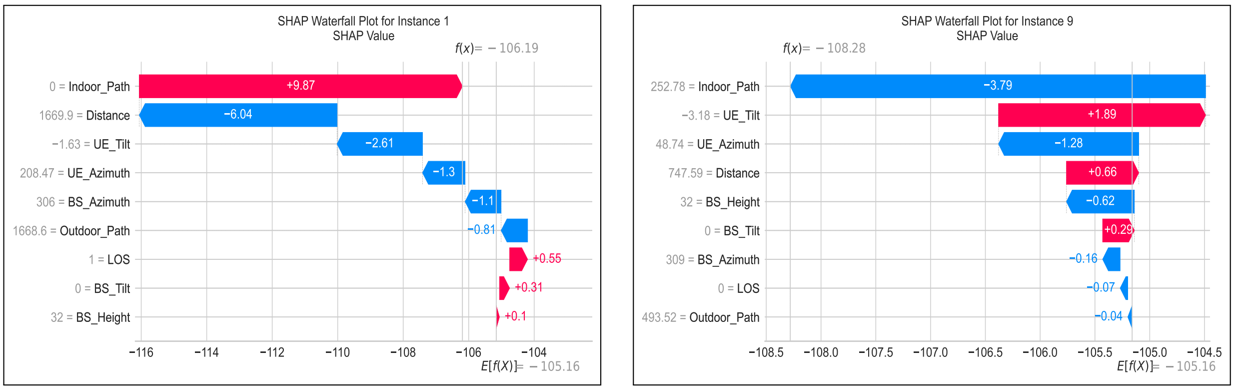


Figure 4: SHAP waterfall plot to highlight the local interactions in data driven propagation modeling.

with lower BS_Azimuth values, and conversely, negative SHAP values when paired with higher BS_Azimuth values. This interaction suggests that the alignment between the user equipment and base station azimuth angles plays a critical role in the model's predictions, affecting signal strength and quality.

SHAP Dependence Plot for UE_Tilt Finally, The SHAP dependence plot for UE_Tilt in Figure 3d shows the relationship between the UE_Tilt and the SHAP values, with color representing the base station azimuth BS_Azimuth. The plot indicates that as UE_Tilt values decrease (tilting downward), the SHAP values generally increase, showing a positive impact on the model's prediction. However, there is a noticeable interaction effect with BS_Azimuth, where the impact of UE_Tilt varies significantly depending on the azimuth angle of the base station. This suggests that the orientation of the user equipment relative to the base station is crucial, with specific tilts being more favorable for signal reception based on the base station's azimuth.

2.3 Local Interpretability Parameters

Local interpretability focuses on explaining the predictions of individual instances within a dataset, providing insights into the specific factors that influence each unique prediction. This level of interpretability is crucial for understanding and validating the decision-making process of machine learning models, especially in applications where transparency and trust are essential. SHAP provides this, in the form of waterfall (Figure 4), and force plots (Figure 5), by detailing how each prediction is derived from the contributions of the model's input variables. This approach is highly intuitive, yielding clear and informative explanations that illuminate the impact of each feature on a specific prediction.

2.3.1 Waterfall Plots

The SHAP waterfall plot depicted in Figure 4 provides an intuitive breakdown of the model's prediction for a single data instance, specifically instance 1. This plot visually illustrates how each feature contributes to the final prediction by showing the cumulative effect of each feature's SHAP value, starting from the base value. The base value ($E[f(X)]$) represents the mean prediction of the model when no features are considered. For this instance, the base value is -105.16. The final prediction for this instance ($f(x)$) is -106.19. The plot displays the contributions of various features to the final prediction. Each feature either adds to or subtracts from the base value, with positive SHAP values indicating an increase and negative SHAP values indicating a decrease in the prediction. The bars are color-coded for clarity: red bars represent positive contributions, and blue bars represent negative contributions. For instance, the feature Indoor Path has the most significant positive impact, adding $+9.87$ to the base value. This indicates that the presence of indoor paths significantly increases the predicted value. On the other hand, the Distance feature has a substantial negative impact, reducing the prediction by -6.04. This suggests that greater distances negatively influence the signal strength. The UE Tilt feature contributes -2.61 to the prediction, indicating a negative effect, while the UE Azimuth feature also has a negative contribution, reducing the prediction by -1.3. Similarly, the BS Azimuth feature has a minor negative effect, reducing the prediction by -1.1. Conversely, the Outdoor Path feature slightly increases the prediction by $+0.81$, indicating a small positive impact. The LOS (line-of-sight) condition reduces the prediction by -0.05, suggesting a minor negative influence. The BS Tilt feature contributes a small positive value of $+0.31$, while the BS Height feature adds a minor positive effect of $+0.1$.

The SHAP waterfall plot depicted in Figure 4(b) provides a detailed breakdown of the model's prediction for data instance 9. This plot visually demonstrates how each feature contributes to the final prediction by showing the cumulative effect of each feature's SHAP value, starting from the base value. The base value ($E[f(X)]$) represents the mean prediction of the model when no features are considered. For this instance, the base value is -105.16. The final prediction for this instance $f(x)$ is -108.28. The plot displays the contributions of various features to the final prediction. Each feature either adds to or subtracts from the base value, with positive SHAP values indicating an increase and negative SHAP values indicating a decrease in the prediction. The bars are color-coded for clarity: red bars represent positive contributions, and blue bars represent negative contributions.

For instance, the feature Indoor Path has the most significant negative impact, subtracting -3.79 from the base value. This indicates that the presence of indoor paths significantly decreases the predicted value. On the other hand, the UE Tilt feature has a substantial positive impact, adding $+1.89$ to the prediction. This suggests that the tilt of the user equipment positively influences the signal strength. The UE Azimuth feature contributes -1.28 to the prediction, indicating a negative effect, while the Distance feature also has a positive contribution, increasing the prediction by $+0.66$. Similarly, the Outdoor Path feature has a minor negative effect, reducing the prediction by -0.04. Other features such as BS Height and BS Tilt have smaller impacts, adding $+0.29$ and -0.07 respectively. The BS Azimuth feature has a negative contribution of -0.62, while the LOS (line-of-sight) condition contributes -0.16.

2.3.2 Force Plots

SHAP force plots are powerful visual tools for understanding the local interpretability of machine learning models. They provide a detailed, instance-specific breakdown of how each feature contributes to the final prediction. By visualizing the additive contributions of features to a model's output, force plots highlight the positive and negative impacts of each feature, offering a clear and intuitive explanation of individual predictions. This is particularly valuable in applications where transparency and trust are critical, such as in healthcare, finance, and communication systems. Force plots facilitate the identification of key drivers behind predictions, enabling users to validate model behavior, detect biases, and make informed decisions.

The SHAP force plots for instances 1 and 9 provide a visual representation of how each feature contributes to the final prediction. These plots highlight the positive and negative impacts of each feature on the model's prediction, making it easier to understand the decision-making process.

For instance 1, the SHAP force plot shows the contributions of various features to the final prediction. The base value, $E[f(X)]$, represents the mean prediction of the model, which is -105.16. The final prediction for this instance, $f(x)$, is -106.19. In this plot, the features are color-coded: red indicates features that increase the prediction, while blue indicates features that decrease the prediction. The width of each bar corresponds to the magnitude of the feature's contribution. For example, the feature LOS increases the prediction by $+1.0$, while the feature Indoor Path has no impact on the prediction, contributing 0.0. The Distance feature significantly decreases the prediction by -1669.9, and the UE Tilt reduces the prediction by -1.63. Similarly, the UE Azimuth decreases the prediction by -208.47, and the BS Azimuth decreases it by -306.0. The plot clearly shows that the Distance feature has the most substantial negative impact on the prediction, followed by the UE Azimuth and BS Azimuth features.

For instance 9, the SHAP force plot similarly shows the contributions of various features to the final prediction. The base value, $E[f(X)]$, is -105.16, while the final prediction for this instance, $f(x)$, is -108.28. In this case, the BS Tilt feature has no impact on the prediction, contributing 0.0, while the Distance feature significantly decreases the prediction by -747.59. The UE Tilt reduces the prediction by -3.18, whereas the Indoor Path increases the prediction by $+252.78$. The UE Azimuth increases the prediction by $+48.74$, and the BS Height increases it by $+32.0$. In this plot, the Distance

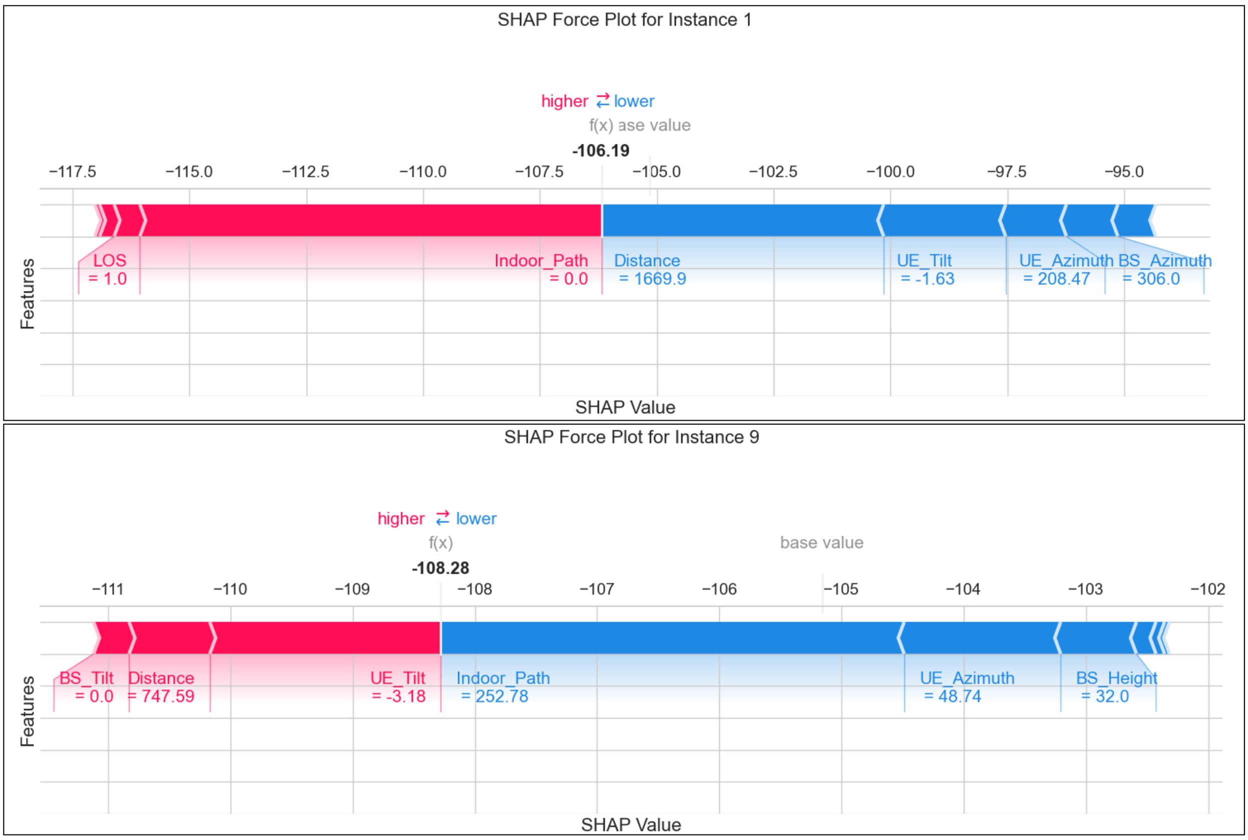


Figure 5: SHAP force plot to highlight the local interactions.

feature again shows a significant negative impact, while the Indoor Path feature has a substantial positive contribution.

3 Conclusion

The advent of 5G and the imminent arrival of 6G technologies have introduced unprecedented complexity to wireless networks. Traditional propagation models, based on empirical or semi-empirical formulas, often fail to capture the intricate interactions between radio waves and the environment, posing significant challenges for network planning and optimization. In response, data-driven models leveraging large datasets and advanced machine learning techniques have emerged as powerful alternatives, offering superior accuracy and efficiency.

In this study, we employed SHAP analysis to enhance the interpretability of data-driven propagation models. By incorporating diverse features such as environmental characteristics, user equipment configurations, and base station parameters, our model delivered highly accurate predictions. SHAP summary plots and dependence plots provided a comprehensive understanding of feature importance and interactions, while waterfall plots offered detailed insights into how individual features contribute to specific predictions. This level of interpretability is crucial for validating model predictions, diagnosing issues, and building trust in AI systems, paving the way for more reliable and efficient wireless communication networks in the 5G and beyond era.

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