A Domain-Aware Framework for Interpretable and Resilient Propagation Models: Enabling Digital Twins for Wireless Networks

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Abstract—**In the rapidly evolving landscape of wireless networks, accurate and resilient propagation models are essential to achieve optimal performance and reliability. This paper presents a novel domain-aware framework for interpretable and resilient propagation models. The proposed approach represents an innovative architecture framework that is not only interpretable but can also deal with training data size scarcity. Bridges domain knowledge with machine learning. The proposed approach leverages a combination of domain expertise, analytical modeling, and customized neural networks to construct interpretable models that excel in both identical distribution and non-identical distribution test-train dataset scenarios. Through a comprehensive analysis, we demonstrate the proposed approach's ability to adapt and refine models in response to real-world variations, ensuring consistent, high-quality performance. The proposed framework not only enhances our understanding of complex systems but also paves the way for the creation of digital twins for wireless networks. Furthermore, the root mean square error of the performance metric for the proposed approach is reported as** 6.97 **dB, further confirming its effectiveness in accurately predicting the results of wireless propagation.**

Index Terms—**Digital Twins, Neural Networks, Radio Propagation Modeling, Resilience Analysis.**

I. Introduction

In the rapidly advancing landscape of wireless networks, the integration of digital twins (DT) emerges as the cornerstone of Industry 4.0, particularly in the context of emerging cellular networks [1]. A DT, serving as a dynamic software replica of the mobile network, proves instrumental in continuous prototyping, testing, and optimization. Its significance becomes pronounced in its ability to design and optimize operations precisely, thereby enhancing overall network efficiency. Beyond simulation, DT acts as a pivotal staging environment for testing AI algorithms before they get deployed in the production environment, ensuring the robustness of these algorithms before deployment in scenarios with limited real network data.

Integral to the successful implementation of a DT for wireless networks is the development of propagation models that exhibit characteristics such as being interpretable and resilient and seamlessly integrating with the physical wireless network [2]. Traditional propagation models, which encompass empirical, deterministic, and stochastic approaches, have historically struggled to meet these characteristics. Ray-tracing-based simulations, although providing acceptable results, fall short in being computationally efficient, particularly when considering the dynamic nature of wireless systems. On the contrary, computationally efficient approaches such as COST-Hata and ITU-R P.453-15, may compromise realistic results [3]. Recognizing the limitations inherent in these traditional approaches, there is growing interest in resilient and adaptive propagation models. This has led to the emergence of data-driven machine learning (ML) techniques and deep neural networks (DNNs). Although ML-based approaches present promising solutions, they introduce a new set of challenges. Challenges in ML-based approaches include the scarcity, incompleteness, and limited accessibility of crucial data to model system behavior across various domains. The black-box nature of conventional ML methods poses interpretability challenges, especially in domains where transparent decision-making is essential. Additionally, the complex mathematical relationships that govern the interaction between the configuration and optimization parameters (COP) and the key performance indicators (KPIs) in wireless networks add another layer of complexity.

This paper navigates through the intricacies of propagation modeling, shedding light on the shortcomings of traditional methodologies, and delving into the promises and challenges associated with ML-based techniques. We introduce a domain-aware framework for interpretable and resilient propagation models, as a transformative solution poised to bridge the interpretability gap and contribute to the realization of robust DTs for wireless networks. This ensures the robustness of AI algorithms before deployment, particularly in scenarios with limited real network data.

A. Related Works

In the field of ML to model the propagation of wireless networks and the prediction of path loss, various studies have made notable contributions. For example, [3] introduces a path loss prediction model that surpasses traditional methods in accuracy and efficiency but lacks a discussion of generalizability and real-world challenges. The work in [4] develops an ML-based propagation model for the prediction of the received power of the reference signal (RSRP), considering factors such as the layout of the building. Limitations include the need for diverse validation and the lack of discussion of interpretability in real-world scenarios. In [5], a combination prediction model for very high-frequency radio wave propagation is presented, outperforming existing models in accuracy and robustness. However, interpretability is not discussed, with a focus on improving accuracy and robustness.

The authors in [6] propose an ML-based approach for the prediction of received signal strength and the evaluation of coverage, highlighting the cost-effectiveness of mobile network planning. However, the paper lacks a discussion of interpretability and challenges related to data distribution or scarcity. Although [7] underscores the importance of interpretability, it lacks a comprehensive discussion of challenges related to predictor coalitions and general model interpretability. In [8], an interpretable NN configures software-defined meta-surface tiles, providing the use of economic resources. Limitations include interpretability, data scarcity, and distribution challenges. The model in [9] predicts wireless coverage using crowd-sourced data and the SHapley Additive exPlanations (SHAP) framework for improved interpretability. Limitations include potential data biases that affect generalizability. Data-driven ML faces the challenges highlighted in [10], including the demand for large datasets and issues such as data scarcity, unrepresentative characteristics, and generalizability of the model.

Persistent challenges include accurate path loss estimation in diverse scenarios, real-world implementation hurdles, and the interpretability of ML models. Scarcity, unrepresentative, and unbalanced data of the real wireless network contribute to biased models struggling with generalizability, known as *distribution shift* [11]. The distribution shift compromises the generalizability of the model, emphasizing the need for robust modeling techniques. Understanding these challenges is crucial for resilient solutions in the modeling of propagation of emerging wireless networks. Currently, there is a notable gap in research that focuses on interpretable and resilient propagation modeling for these networks, especially using tabular data-driven approaches. *In summary, current works on propagation modeling fail to address realistic challenges such as distribution shift, data scarcity, and model interpretability.*

B. Contributions

In this challenging context, our aim is to fill the identified literature gap. We present a novel, domain-aware, interpretable, and resilient ML model framework designed for the complexities of real-world wireless networks, addressing issues such as model insights, sparsity and scarcity of training data, and unrepresentative distribution shifts in test data. The primary contributions can be outlined as follows:

- A novel domain-aware propagation modeling framework is introduced for predicting the RSRP. Unlike traditional models, our framework incorporates domain knowledge to construct an initial mathematical model, making it more effective in capturing complex environments.
- A framework is designed that is interpretable, allowing users to understand how the model arrives at its predictions. We demonstrate how our framework shows remarkable resilience, maintaining its predictive accuracy even when faced with test data distributions that are entirely unknown and differ from the training data distributions. This resilience is crucial in practical applications where data variability is common.
- The robustness of our proposed framework is demonstrated. Unlike data-driven ML models that often suffer from reduced performance as training data becomes sparse, proposed approach exhibits robustness to variations in the amount of training data. This robustness ensures reliable predictions even when data availability is limited.

II. Proposed Framework: Domain-Knowledge-Based Model Construction, Training, and Testing

A. A Brief Overview of Various Modules in the Framework

The proposed approach is a synergy of domain knowledge, analytical modeling, and ML, as shown in Fig. 1. The initial phase, *Data Generation* (M1 in Fig. 1), involves creating raw data for model training and testing, derived from network simulators or directly from network operators. Following this, the *Feature Engineering* module (M2 in Fig. 1) processes this raw data into engineered data by selecting key network topological and geographical parameters, such as antenna configurations (tilt, azimuth, height) and terrain features (ground and building heights). Concurrently, the *Model Construction* module (M3 in Fig. 1) develops a custom NN architecture, leveraging domain knowledge and data insights. This process begins with the establishment of a foundational COP-KPI relationship, leading to an analytical equation that guides the design of our NN model for KPI predictions. This equation informs the selection of observable variables, mathematical operations, activation functions, and network layers tailored to our model. Subsequently, in the *Model Training* module (M4 in Fig. 1), the NN undergoes training at various levels of data scarcity. The final step, *Model Resilience Testing*, critically evaluates the efficacy of the trained model on test data, evaluating performance across both identical distribution (ID) and non-identical distribution (NID) scenarios.

B. Data Collection, Feature Engineering (M1-M2 in Fig. 1)

The raw dataset encompasses essential information related to signal propagation and is organized into three primary categories: (1) base station (BS) site-specific details, including location and antenna specifications; (2) geographic information, including terrain, building structures, and land cover data; and (3) UE measurements, including RSSI values, location coordinates, and network-specific details. Using domain knowledge, we employ feature engineering in our raw dataset to systematically transform the raw site-specific, geographic, and UE data of the BS into features. These features comprise

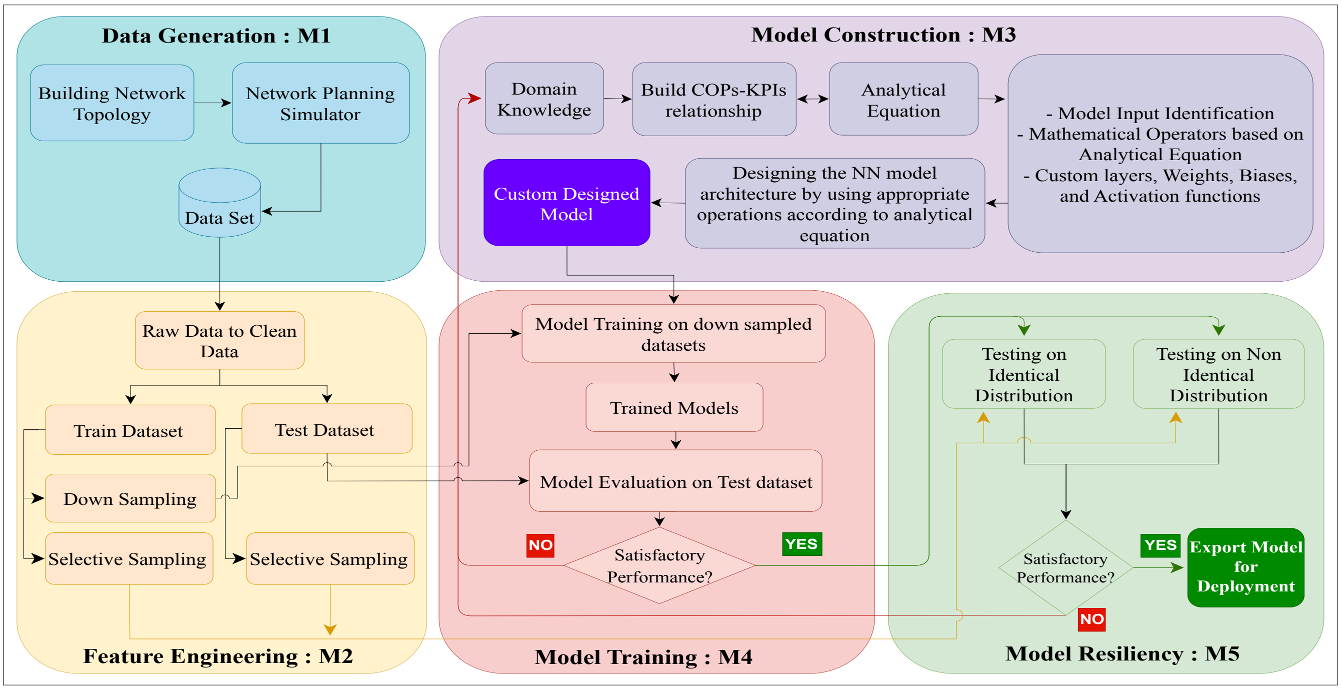

Fig. 1: The proposed framework for data-driven custom neural architecture model. In addition to the Data Generation (M1) and Feature Engineering (M2) modules, Model Construction, Training, and Resilience Testing are summarized in M3, M4, and M5, respectively.

distances, clutter information, building penetrations, diffraction points, and angular separations between BS and UE.

C. Construction of Proposed Neural Architecture (M3)

1) Domain Knowledge based Analytical Equation: From the domain knowledge of wireless communication, we can illustrate the proposed approach using the simplest indicator of coverage, RSRP, this can be written as follows;

$$P_r[\text{dBm}] = P_t - PL + G - L + X, \tag{1}$$

where, P_r is the received power, P_t refers to the transmit power of the BS, PL refers to the path loss, G represents antenna gain, L represents attenuation caused by clutter (building, trees, etc), X includes additional losses from BS cable and equipment. To calculate the PL for (1), we utilize the path loss model for the 3D UMa scenario from the WINNER II channel models of IST-4 $-$ 027756 [12], which shows that PL is the maximum of the path losses in the LoS and NLoS scenarios, that is, $PL[dB] = \max(PL_{LOS}, PL_{NLOS})$. These scenarios are functions of distance d, carrier frequency f_c, BS height, h_{bs}, UE height, h_{ue},

$$\begin{aligned} PL_{LOS}(d, f_c, h_{bs}, h_{ue}) &= 40\log_{10}(d) + 6\log_{10}(f_c/5) \\ &- 14\log_{10}(h_{bs}) + 13.47 - 14\log_{10}(h_{ue}). \end{aligned} \tag{2a}$$

For NLOS, the path loss is a function of all the above parameters except UE height, as shown below,

$$\begin{aligned} PL_{NLOS}(d, h_{bs}, f_c) &= \log_{10}(d)[44.9 - 6.55\log_{10}(h_{bs})] \\ &+ 5.83\log_{10}(h_{bs}) + 23\log_{10}(f_c/5) + 34.46. \end{aligned} \tag{2b}$$

According to the 3GPP recommendation [13] the antenna gain G for (1), is the product of maximum antenna gain, G_{max}, and antenna attenuation, A_{att}, i.e., $G = G_{max} \cdot A_{att}$. The G_{max} is dependent on antenna efficiency ζ, horizontal and vertical beamwidths B_h, B_v, and related to antenna directivity as.

$$G_{\max}(B_h, B_v, \zeta) = \zeta D = \zeta\frac{4\pi}{B_h B_v}. \tag{3}$$

The antenna attenuation is written as follows;

$$\begin{aligned} &A_{att}(B_h, B_v, \phi_u, \phi_{tilt}, \theta_u, \theta_{azi}, \lambda_h, \lambda_v, A_h, A_v)\,[\text{dB}] = \\ &\lambda_v \min[12(\frac{\phi_u - \phi_{tilt}}{B_v})^2, A_v] + \lambda_h \min[12(\frac{\theta_u - \theta_{azi}}{B_h})^2, A_h]. \end{aligned} \tag{4}$$

Where, B_h and B_v represent the horizontal and vertical half-power beam widths. θ_u, θ_{azi} represents the azimuth angles, whereas, ϕ_u, ϕ_{tilt}, represents the tilt angles for BS and UE. λ_h and λ_v represent the weighting factors for the beam pattern in both directions. The vertical and horizontal maximum attenuation for the sides and back of the bore sight is indicated by A_h, and A_v, respectively. Henceforth, placing (2a), (2b), (3), and (4) back into (1) the complete analytical equation for calculating the RSRP coverage for the UE as a function of several *COPs* can be written as in (5).

2) Formulating Custom NN Using Analytical Equations: After deriving the analytical equation, i.e. (5), our focus shifts towards creating the architecture of the NN. In contrast to conventional DNN architectural methodologies, where a sequential model is incrementally expanded with layers and specified neuron counts, often utilizing ReLU as the default activation function, our approach takes a distinctive path. We design the architecture based on an acquired domain-based

$$P_r\left(d, f_c, h_{bs}, h_{ue}, \zeta, B_v, B_h, A_v, A_h, \phi_u, \phi_{tilt}, \theta_u, \theta_{azi}, \lambda_h, \lambda_v\right) = P_t + 84.9\log_{10}(d) + 29\log_{10}\left(f_c/5.0\right) - 19.83\log_{10}\left(h_{bs}\right) - 14\log_{10}\left(h_{ue}\right) - 6.55\log_{10}(d)\log_{10}\left(h_{bs}\right) + 10\log_{10}\left(\zeta\frac{4\pi}{B_v B_h}\right) - \lambda_v \min\left(12\left(\frac{\phi_u - \phi_{tilt}}{B_v}\right)^2, A_v\right) - \lambda_h \min\left(12\left(\frac{\theta_u - \theta_{azi}}{B_h}\right)^2, A_h\right) - L + X + 47.93 \quad (5)$$

analytical equation, where every aspect, from selecting input variables to determining the activation function, is guided by a profound understanding of the underlying system equation. This innovative approach involves constructing the NN directly from the analytical equation, representing a departure from typical methodologies. While current approaches introduce domain knowledge by embedding loss terms in the form of approximation constraints within the baseline DNN structure, our proposed methodology is inherently distinct. By adopting this approach, we aim to offer users a transparent insight into the internal workings of the NN—a departure from the prevailing 'black box' nature of DNN.

The first step involves identifying the input variables derived from the analytical (5), which include ζ, A_v, A_h, ϕ_u, ϕ_{tilt}, θ_u, θ_{azi}, B_v, B_h, h_{bs}, h_{ue}, f, d, λ_h, and λ_v. The second step entails recognizing the mathematical relationships, represented by various operators, that connect these variables. These operators encompass addition, subtraction, multiplication, logarithmic functions, division, squaring, minimum, and maximum. In the third step, custom-written activation functions are developed for each layer to align with the desired output type. To implement this, the Keras API is used to construct the different layers of the NN model. Keras facilitates the incorporation of various mathematical operations, including those identified in the second step.

D. Model Training and Resilience Testing (M4, M5)

In this module, we outline our methodology for evaluating and comparing the performance of the proposed approach with the conventional method. We begin by constructing a propagation modeling training dataset, which incorporates a diverse range of geographic and network features, as detailed in section II-B. As mentioned previously in section I, acquiring training data for experimental or optimization purposes in wireless communication systems often presents multiple challenges. Network engineers often encounter challenges due to the scarcity of training data, resulting in limited variability. This scarcity can compromise the quality of the training data and consequently impact the effectiveness of model training. Recognizing these practical impediments, our analysis aims to systematically evaluate both the proposed and conventional approaches across multiple sets of training dataset sizes. Through this analysis, we seek to gain insights into the performance characteristics of each approach under varying data constraints. We refer to them as data scarcity challenges.

In addition, model resilience testing is conducted in two distinct ways. Firstly, the conventional ID approach involves maintaining the distribution of test data as identical to that of the training data. In the second approach, we introduce various NID test scenarios for resilience analysis. For this purpose, we use SHAP sensitivity analysis and identify the most important features using the LightGBM model—a widely acknowledged model in propagation model literature for SHAP analysis. The top three influential features, ranked in descending order, are identified as follows: $F1$: "Distance", $F2$: "UE Tilt", and $F3$: "BS Azimuth". Subsequently, the distributions of these features are discretized into a histogram of bin widths as 12 & 18. NID test scenarios are created by selectively sampling train data from either the upper or lower regions/bins of the histogram. The objective of this testing is to verify that the proposed model exhibits resilience in handling unrepresentative and imbalanced datasets. The purpose of this selective sampling is to highlight the kind of experience that network operators face when collecting network data required for planning and optimization purposes. One main challenge, as mentioned in [10], is the sparsity of diverse datasets for training and testing models in real wireless networks. Existing data is often limited and skewed due to factors such as location density and environmental variations [14], [15]. For instance, urban areas contribute more data, creating a bias towards urban signal patterns in models. As mentioned in section I-A this bias leads to *distribution shift* in data.

III. Simulation Setup and Performance Evaluation

A. Experimental Setup

We have utilized Atoll [16], a 3D ray tracing-based network planning tool, to model the network environment that covers an area of 3.8 square kilometers with 10 eNodeB macrocell in the center of Brussels, Belgium. We divide the area into bins and calculate the RSRP values for each bin by averaging the RSRP values of the users in the area. Table I summarizes the key simulation parameters adopted for this study.

Table I: Key Simulation Parameters Values

Parameter	**Value/Type**
Path loss model	Aster propagation (ray-tracing)
eNodeB height [m]	28-37
Antenna tilt [°]	0-6
Antenna azimuth [°]	41-319
Antenna gain	18.3 dBi
Horizontal half power beamwidth	65°
Vertical half power beamwidth	9°
eNodeB max transmit power [dBm]	43

B. Model RMSE performance against Training Data Scarcity

As detailed in section II-D, a key focus of this work is to assess and compare model performance under extremely limited training datasets. In this regard, We evaluated and compared the performance of the RMSE of the baseline and the proposed approach in different sizes of training data, as illustrated in the spider diagram in Fig. 2. The baseline DNN architecture used for the comparison consists of a sequential model with several layers. The first layer, with 14 neurons, takes input features from the training data and applies the rectified linear unit (ReLU) activation function. Subsequently, two hidden layers with 64 neurons each follow, both using the ReLU activation function. Another hidden layer with 128 neurons and ReLU activation is added before the final layer, which consists of a single neuron with linear activation.

The analysis begins with a data set of sizes $40,000$, various percentages of this size are considered to create cases with varying scarcity levels. RMSE values are represented by concentric circles in Fig. 2, which exhibit an increasing trend as the radial axes extend outward. The comparison between the baseline and the proposed approach indicates that the latter not only achieves lower RMSE values for cases with low scarcity but also maintains its performance in high-scarcity situations. In contrast, while the baseline approach demonstrates performance comparable to that of the proposed approach for low-scarcity cases, a significant decrease in performance is observed in extremely high-scarcity situations. This comparison emphasizes that the proposed approach outperforms the baseline approach by a substantial margin, particularly in high-scarcity scenarios. This tendency is commonly observed in black-box NN, which tends to overfit with limited training data. This is evident in Fig. 2, where the level of the proposed approach performance remains unaffected in the face of limited training data, in contrast to the baseline DNN, which shows a performance decline under similar conditions. Despite the reduction in the size of the training data, the proposed approach maintains relatively robust performance, reflected in an RMSE of 7.46 dB. Importantly, this value does not show a significant increase compared to the RMSE of 6.97 dB observed in a scenario with abundant training data, which demonstrates only a performance drop of 6.4%.

C. Resilience Performance of Proposed Framework

Here we discuss the resilience performance of baseline and the proposed approach. For this purpose, we have discretized the distribution of identified features into histograms of bin sizes 12 and 18, as discussed in section II-D. In the ID case, where the distribution of test data mirrors that of the training data, both models demonstrate comparable performance, with marginal differences observed in their RMSE values. However, when subjected to NID scenarios characterized by selectively sampled training data from distinct regions of the feature histogram, noteworthy variations in performance emerge.

For instance, when considering the feature of Distance with a bin size of 12, the proposed NN exhibits superior resilience compared to the baseline DNN in the NID case, achieving a lower RMSE value of 6.71 dB compared to 52.21 dB for the baseline model. This trend is consistent across other feature-bin combinations, suggesting that the proposed NN is better equipped to handle unrepresentative and imbalanced datasets, as evidenced by its ability to maintain lower RMSE values across various NID scenarios.

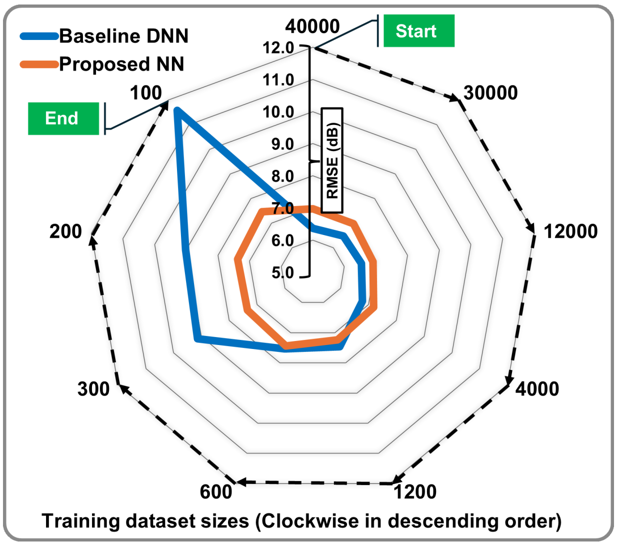

Fig. 2: RMSE evaluation of proposed and baseline schemes across decreasing training dataset sizes. The radar plot displays the transition from 40000 training data points to 100 data points in a clockwise direction, with ascending RMSE values indicated by inner circles. This result shows that the baseline faces high RMSE with limited training data, whereas the proposed approach remains consistent.

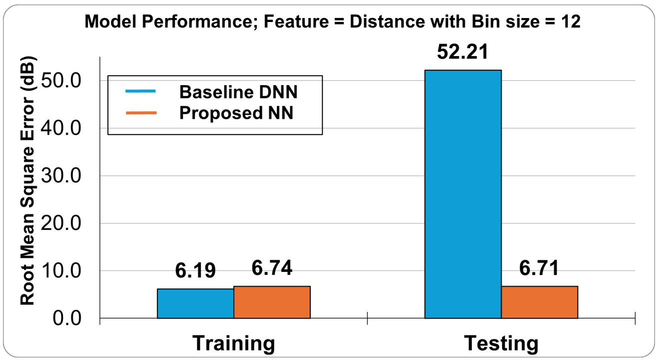

Fig. 3: Comparison of baseline and proposed models' performance in predicting RSRP, using histogram-based discretization of Distance feature. The proposed model shows significant improvement over the baseline during testing.

Interestingly, the performance disparity between the baseline and proposed models becomes more pronounced with an increased bin size, particularly evident in the feature of UE Tilt. In the NID case with a bin size of 18, the proposed NN achieves significantly lower RMSE values compared to the baseline DNN, highlighting its enhanced adaptability to datasets characterized by larger bin widths and greater variability. Moreover, when examining the feature of BS Azimuth, the proposed NN demonstrates a noteworthy improvement in performance compared to the baseline model in the NID case, particularly evident with a bin size of 18. Here, the proposed NN achieves an RMSE value of 7.75 dB, significantly outperforming the baseline DNN's RMSE value of 82.75 dB.

Overall, these results underscore the effectiveness of the proposed NN model in addressing the challenges posed by data

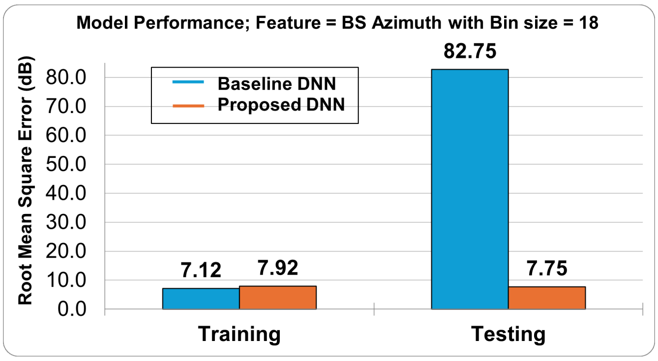

Fig. 4: Comparison of baseline and proposed models' performance in predicting RSRP, using histogram-based discretization of BS Azimuth feature. The proposed model shows significant improvement over the baseline during testing.

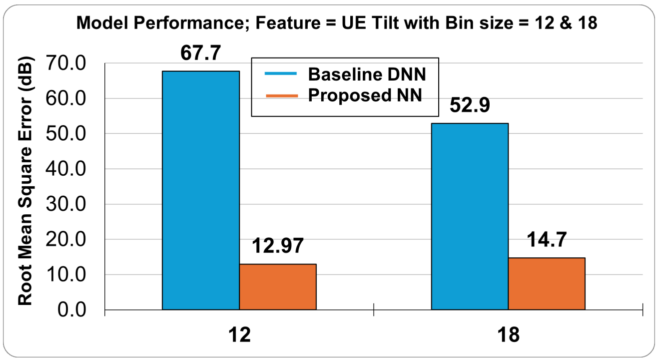

Fig. 5: Comparison of baseline and proposed models' performance in predicting RSRP, using histogram-based discretization of UE Tilt feature. The proposed model shows significant improvement over the baseline during testing in both sizes (12 and 18).

scarcity and distribution shifts in real-world wireless network scenarios. The model's robust performance across varying degrees of data scarcity and feature distributions attests to its potential utility in practical applications, offering promising prospects for enhancing network planning and optimization processes.

IV. Conclusion and Future Works

The proposed approach offers a unique combination of interpretability and resilience, making it an exceptional solution for wireless network modeling. It outperforms traditional black-box DNN models, especially in scenarios with limited data. Its adaptability is improved by simplified hyperparameter determination and the elimination of prior system knowledge requirements. Providing explicit mathematical equations ensures transparency and optimization insights. This innovative framework bridges domain knowledge and machine learning, offering reliable models tailored to evolving networks. Future work could explore integration into 6G networks and extension to millimeter-wave frequencies, alongside comprehensive validation in real-world environments.

References

[1] Han, Bin and Habibi, Mohammad Asif and Richerzhagen, Bjoern and Schindhelm, Kim and Zeiger, Florian and Lamberti, Fabrizio and Pratticò, Filippo Gabriele and Upadhya, Karthik and Korovesis, Charalampos and Belikaidis, Ioannis-Prodromos and Demestichas, Panagiotis and Yuan, Siyu and Schotten, Hans D., "Digital Twins for Industry 4.0 in the 6G Era," *IEEE Open Journal of Vehicular Technology*, vol. 4, pp. 820–835, 2023.

[2] A. A. Puspitasari, T. T. An, M. H. Alsharif, and B. M. Lee, "Emerging Technologies for 6G Communication Networks: Machine Learning Approaches," *MDPI Sensors*, vol. 23, p. 7709, Sep 2023.

[3] U. Masood, H. Farooq, and A. Imran, "A Machine Learning Based 3D Propagation Model for Intelligent Future Cellular Networks," in *2019 IEEE Global Communications Conference (GLOBECOM)*, (Waikoloa, HI, USA), pp. 1–6, December 2019.

[4] S. Wu, B. Ma, T. Ye, J. Zhang, W. Shao, and W. Zheng, "A Machine Learning based Intelligent Propagation Model for RSRP Prediction," in *2022 International Seminar on Computer Science and Engineering Technology (SCSET)*, (Indianapolis, IN, USA), pp. 1–5, 2022.

[5] J. Wang, Y. Hao, and C. Yang, "A Comprehensive Prediction Model for VHF Radio Wave Propagation by Integrating Entropy Weight Theory and Machine Learning Methods," *IEEE Transactions on Antennas and Propagation*, vol. 71, pp. 6249–6254, July 2023.

[6] L. Dai and H. Zhang and Y. Zhuang, "Propagation Model Free Coverage Evaluation via Machine Learning for Future 5G Networks," in *2018 IEEE 29th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, (Bologna, Italy), pp. 1–5, 2018.

[7] G. Reus-Muns, J. Du, D. Chizhik, R. Valenzuela, and K. R. Chowdhury, "Machine Learning-based mmWave Path Loss Prediction for Urban/Suburban Macro Sites," in *GLOBECOM 2022 - 2022 IEEE Global Communications Conference*, pp. 1429–1434, 2022.

[8] C. Liaskos, A. Tsioliaridou, S. Nie, A. Pitsillides, S. Ioannidis, and I. Akyildiz, "An Interpretable Neural Network for Configuring Programmable Wireless Environments," in *2019 IEEE 20th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, (Cannes, France), pp. 1–5, IEEE, 2019.

[9] A. Ghasemi, "DATA-DRIVEN PREDICTION OF CELLULAR NETWORKS COVERAGE: AN INTERPRETABLE MACHINE-LEARNING MODEL," in *2018 IEEE Global Conference on Signal and Information Processing (GlobalSIP)*, pp. 604–608, 2018.

[10] V. P. Rekkas, S. Sotiroudis, P. Sarigiannidis, S. Wan, G. K. Karagiannidis, and S. K. Goudos, "Machine Learning in Beyond 5G/6G Networks—State-of-the-Art and Future Trends," *Electronics*, vol. 10, p. 2786, 2021.

[11] M. Zhang, *Adaptation Based Approaches to Distribution Shift Problems*. PhD thesis, EECS Department, University of California, Berkeley, December 2021.

[12] J. Meinilä, P. Kyösti, T. Jämsä, and L. Hentilä, *WINNER II Channel Models*, ch. 3, pp. 39–92. John Wiley & Sons, Ltd, 2009.

[13] 3rd Generation Partnership Project, "TR36.814 v9.0.0: Further Advancements for E-UTRA Physical Layers Aspects (Release 9)," Technical Report TR36.814 v9.0.0, 3GPP, Sophia Antipolis, France, March 2010.

[14] M. Chen, Y.-C. Liang, and H.-H. Chen, "Machine Learning for Wireless Networks with Artificial Intelligence: A Comprehensive Survey," *IEEE Access*, vol. 6, pp. 36114–36134, 2018.

[15] H. N. Qureshi, U. Masood, M. Manalastas, S. M. A. Zaidi, H. Farooq, J. Forgeat, M. Bouton, S. Bothe, P. Karlsson, A. Rizwan, *et al.*, "Towards Addressing Training Data Scarcity Challenge in Emerging Radio Access Networks: A Survey and Framework," *IEEE Communications Surveys & Tutorials*, 2023.

[16] Forsk, "Atoll Overview." Accessed on: March 11, 2024 [Online]. Available: https://www.forsk.com/atoll-overview.