Wireless communication channel modeling based on ML

Yiheng Shi[1,6,†], Weiqi Zhu[2,7,†], Xuanyu Chen[3,5,8,†], Yuxuan Zhong[4,9,†]

[1]School of Art and Science, Rutgers, the state university of New Jersey, New Brunswick, 08901, US
[2]School of Electrical Information Engineering, Jiangsu University of Technology, Changzhou, 213001, China
[3]Department of Electronic and Computer Engineering, The Hong Kong University of, Science and Technology, Hongkong, 999077, China
[4]International School, Beijing University of Posts and Telecommunications, Beijing, 100876, China
[5]Corresponding author

[6]shiyiheng0302@gmail.com
[7]3263713277@qq.com
[8]xchendf@connect.ust.hk
[9]zhongyuxuan0806@163.com
[†]All the authors contributed equally to this work and should be considered as co-first author.

Abstract. Nowadays, wireless communication plays an important role in various fields of our lives, and in order to ensure good communication performance, reliable channel models are important. In this paper, we present a comprehensive survey of Machine Learning (ML) based channel modeling methods to help with the estimation and prediction accuracy on wireless channel modeling. To begin with, we start with a review of the traditional methods of wireless communication channel modeling, basically empirical method and deterministic method. Then, we introduce several ML methods to address limitations of traditional ways will be used for channel modeling, such as Support Vector Machine (SVM), Random Forests, autoencoder, Deep Learning, etc. Lastly, we demonstrate the application of ML methods including deep learning, SVM, and random forests on wireless channel modeling. Through learning the underlying channel distribution, Deep Learning methods have already demonstrated remarkable performance in channel modeling for different scenarios in some previous learning. Also, by training with suitable kernels and conducting sufficient training iterations, optimal hyperplanes can be identified, Support Vector Machines (SVM) can then be utilized to predict channel characteristics based on input features. Random Forests can identify the most relevant features influencing the channel and optimize system design by handling complex and high-dimensional data through iterative feature selection and splitting criteria. These methods achieve competitive accuracy with respect to traditional methods, however, there are still challenges and issues to be addressed in the application of machine learning methods for communication channel modeling.

Keywords: Channel modeling, Wireless communication, Machine Learning, Deep learning

DOI: 10.54254/2755-2721/78/20240462

1. Introduction

In the rapidly evolving digital era, wireless communication has solidified its role as a pivotal driver for technological advancement and societal transformation. From personal devices to intricate global networks, it permeates every facet of our modern existence. This ubiquity not only offers unparalleled convenience and connectivity but also propels societal development, enhancing the overall quality of life.

The essence of reliable communication lies at the heart of these applications, underscoring the imperative need for dependable channel models. These models elucidate the intricacies of signals as they propagate, detailing aspects like path loss, multipath effects, and shadowing. A precise channel model stands as a cornerstone for the design and performance assessment of wireless systems.

Historically, the realm of wireless communication channel modeling has been dominated by traditional methods. However, as communication ecosystems have grown in complexity, there has been a rising demand for more adaptive and flexible modeling techniques. Enter ML - a transformative technology that has reshaped countless industries by extracting meaningful insights from vast amounts of data [1].

ML, with its myriad of algorithms and methodologies, offers a fresh approach to channel modeling. Deep learning, a subset of ML, utilizes neural networks with many layers to analyze various factors affecting signal transmission. Techniques like convolutional neural networks (CNNs) are particularly adept at processing spatial data, making them ideal for understanding the intricate patterns in wireless channels. SVM, on the other hand, can classify and predict non-linear data, offering a robust tool for dynamic channel environments. Random forests, a form of ensemble learning, leverage multiple decision trees to arrive at more accurate and stable predictions.

The efficiency of ML lies not just in its diverse techniques but also in its adaptability. As wireless communication environments continuously evolve, ML models can be retrained and updated, ensuring they remain relevant and accurate. This dynamic nature of ML stands in stark contrast to traditional methods, which often require manual recalibration.

This study aims to provide a systematic review and analysis of conventional wireless communication channel modeling techniques, whilst placing significant emphasis on how ML technologies are revolutionizing and enhancing modeling capabilities within this domain. Traditional methodologies, including geometry-based stochastic models and deterministic ray-tracing techniques, have laid a solid foundation for understanding and predicting the behavior of wireless channels. However, these approaches encounter challenges when dealing with the dynamic and complex nature of channels within highly variable environments. In contrast, ML-particularly advanced techniques such as deep learning, SVM, and random forests-demonstrates an exceptional ability to handle large-scale complex data and to uncover subtle patterns and trends, which is invaluable for channel modeling in wireless communications [2].

Synthesizing existing literature and practical case studies, this research further reveals the strengths of ML-based approaches to wireless communication channel modeling. ML methodologies can automatically adjust model parameters to adapt to environmental changes, thereby improving the generalizability and predictive accuracy of models. Moreover, ML models offer the capability for continuous learning and adaptation with minimal human intervention. This paper not only elaborates on the application of various ML techniques to wireless communication channel modeling but also presents a perspective on their limitations and potential future directions. By integrating traditional models with ML techniques, we aim to provide a robust analytical and predictive tool for researchers and engineers in the field of wireless communications, guiding them in the design and optimization of communication systems.

2. Traditional method on wireless channel modeling

Wireless communication has been widely adopted in various sectors, including military and civilian fields, thanks to its inherent advantages such as mobility, scalability, and convenience. In order to ensure high-quality communication, it is crucial to have accurate channel models that serve as references for theoretical analysis, performance evaluation, and system deployment of wireless communication systems between transmitters and receivers. This section will discuss two traditional methods commonly used for channel modeling.

The channel modeling methods refer to the approaches used to characterize the wireless communication channel in a deterministic or statistical manner. Commonly, wireless communication channel models can be classified into two categories, the empirical models and the deterministic models.

The empirical models are mainly based on observations, extensive measurements, and statistical analysis of real-world wireless environments. This paper discusses three significant empirical models focusing on path loss [1]. The first one is the Hata-Okumura model, which presents urban area propagation loss as a standard formula, along with additional correction factors for application in other situations. Although this model neglects obstacle parameters such as hills and buildings, it performs with high accuracy in urban and suburban environments but may not be suitable for mountainous or densely built-up areas.

As an extension, the European Cooperation for Scientific and Technical Research (COST-231) model was proposed. COST-231 introduces additional environmental parameters and correction factors that focus on frequency dependency, terrain and urban parameters, building effects, as well as damping factors to increase its applicability in urban environments. Comparing the predicted value of COST-231 model with the measured value in a city, the average error of path loss is within ±3 dB and the standard deviation is 5-7 dB. Also, ECC-33 is derived from the Okumura model with some modifications to its assumptions so that it can more closely represent a fixed wireless access system. The ECC-33 model is known to be more accurate in mountainous and suburban environments.

Deterministic models utilize specific geographical and morphological information, as well as electromagnetic wave propagation theory or optical ray theory, to analyze and predict wireless propagation models. Compared to empirical modeling methods, deterministic modeling does not require a large amount of measured data, instead, it only needs a detailed understanding of the propagation environment to make more accurate predictions about signal propagation. Common deterministic modeling methods include ray tracing and finite-difference time-domain (FDTD) method. Wahab Khawaja introduced a study that employed ray tracing to model AG channels in various environments such as urban, suburban, rural, and oversea at 28 GHz and 60 GHz [2]. Furthermore, Mattia Lecci made a great effort to simplify the computational complexity of ray tracing for mmWave channel modeling by limiting the maximum reflection order and removing some low-power multipath components [3]. Zhiyuan Shi employed the FDTD method to simulate the transient impulse response which enabled them to calculate the channel parameters, facilitating the development of a channel model for effective communication between unmanned aerial vehicles (UAVs) and vessels [4].

3. Wireless Communication Channel Modeling with ML Techniques

SVM stand out in the ML landscape for their adeptness at both classification and regression tasks, especially in the domain of channel modeling. At the core of SVMs is the principle of determining an optimal hyperplane that distinguishes data into distinct classes, with ‘optimal’ implying the hyperplane that maximizes the margin between two data sets, thereby minimizing potential misclassification. While they excel at linear classification, real-world channel conditions often introduce non-linear data patterns. Addressing this, SVMs employ the kernel trick, transforming data into a higher-dimensional space where it becomes linearly separable without the computational heft. Various kernel functions, such as the polynomial, radial basis function (RBF), or sigmoid, enable SVMs to cater to diverse non-linear patterns. For instance, in urban environments with varied obstructions, wireless signals encounter multiple states. Trained on data from various environments, SVMs can predict the wireless channel’s state in real-time, facilitating efficient signal processing and resource allocation. Their ability to efficiently delineate both linear and non-linear channel conditions underscore SVMs’ invaluable role in modern communication systems.

Random Forests, as an ensemble learning method, have emerged as a formidable solution to overfitting in channel modeling by harnessing the collective wisdom of numerous decision trees. Each

DOI: 10.54254/2755-2721/78/20240462

tree is cultivated from a distinct subset of training data through bootstrapping, introducing a degree of randomness that equips each tree to capture varied data patterns. For instance, while one tree might excel at understanding signal propagation in urban environments peppered with skyscrapers, another might specialize in the clearer, sparser terrains of the countryside. As predictions are made, rather than relying on individual trees, which may hold specific biases or errors, the Random Forest amalgamates their outputs, typically leaning towards a 'majority vote' approach. This ensemble mechanism inherently smoothens out anomalies and inaccuracies. In practical terms, this means that when dealing with diverse channel conditions, such as those found in mixed urban and rural landscapes, Random Forests can offer holistic and precise insights, making them indispensable in the multifaceted realm of communication systems.

Variational Autoencoders (VAEs), esteemed as generative models, excel at deciphering and learning complex data distributions, a capability crucial for capturing the nuances of channel states in communications [1]. Unlike traditional models that might only offer a surface-level understanding, VAEs delve deep, encapsulating underlying channel state dynamics which can be essential for adaptive communication strategies. On a similar note, autoencoders, characterized by their encoder-decoder architecture, have redefined the landscape of communication systems. More than just reproducing input as output, they've brought transformative changes to the field, especially in end-to-end communication designs [2]. By integrating processes that were traditionally separate, such as signal modulation and demodulation, autoencoders facilitate a cohesive optimization of these tasks. This integrated approach, where both modulation and demodulation schemes are honed simultaneously, ensures that the communication process is not just streamlined but also remarkably efficient, paving the way for more resilient and adaptive systems.

Deep learning's ascendancy in recent years owes much to its unparalleled ability to decipher complex, non-linear relationships. In the realm of wireless channel modeling, DNNs shine particularly in dense urban environments fraught with signal reflections and multi-path fading. CNNs, traditionally associated with image processing, have found utility in spatial data processing within the wireless domain, particularly beneficial for MIMO (Multiple Input Multiple Output) systems where spatial data is paramount. RNNs and their more advanced cousins, LSTMs, are tackling the challenges of mobile communication where data's temporal dimension cannot be ignored, ensuring seamless communication in high mobility scenarios [3].

Dynamics of wireless environments, replete with ever-moving users, rapidly changing topologies, and an ever-increasing density of communicating devices, present a modeling quagmire. Here, reinforcement learning's promise shines brightest. Algorithms like Q-learning are no longer just theoretical constructs but are actively tailoring transmission strategies in real-time. By constantly ingesting environmental feedback, they optimize both beamforming directions and power allocation, ensuring peak performance even in tumultuous conditions.

Emerging paradigms, such as Generative Adversarial Networks (GANs), are revolutionizing channel simulations. By generating synthetic channel conditions, GANs obviate the need for exhaustive real-world data collection, making model training more versatile and comprehensive [4]. Furthermore, the tenets of Federated Learning, advocating decentralized learning while preserving data privacy, dovetail perfectly with wireless communication's inherent structure. This approach promises not just enhanced user privacy but also more efficient models by reducing redundant data transmissions [5].

To conclude, ML's symbiosis with wireless communication channel modeling is crafting a future where communication is not just fast but intelligent, adaptive, and efficient. As technological milestones like 6G loom on the horizon, the confluence of these domains will undoubtedly dictate the trajectory of next-generation communication systems [6, 7].

4. Wireless Communication Channel Modeling Technology Based on Various ML Techniques

4.1. Deep Learning

ML, particularly deep learning, offers significant potential for enhancing wireless communication channel modeling. These models have shown superiority in capturing the complex, non-linear relationships inherent in wireless communication systems, which traditional methods often struggle to handle [8].

A critical application of deep learning is predicting Channel State Information (CSI). Accurate and timely CSI is crucial for optimizing wireless communication performance. Deep learning models, such as convolutional neural networks, have been utilized for CSI prediction. a CNN-based model was proposed to predict future CSI based on historical data, and the results demonstrated significant improvement over traditional methods [9].The model effectively learned the temporal correlation in the CSI, thus enhancing the prediction accuracy.

In the context of millimeter-wave (mmWave) channel modeling, deep learning also presents promising opportunities. mmWave is a key part of 5G and beyond, but its high frequency and susceptibility to blockage create unique challenges for channel modeling [10].proposed a deep learning model based on GANs to accurately model mmWave channels. The GAN was trained to generate channel responses that were statistically similar to the real channel responses, demonstrating the potential of deep learning in this area.

MIMO (Multiple-Input Multiple-Output) channel modeling is another area where deep learning has shown promise. MIMO, which involves using multiple antennas at both the transmitter and receiver, can significantly enhance wireless communication performance. However, it also greatly increases the complexity of channel modeling. A deep learning-based model for MIMO channel estimation is created. The model was designed to learn the underlying channel distribution, leading to more accurate channel estimations and thus improved system performance.

While the potential of deep learning for wireless communication channel modeling is clear, challenges remain. Deep learning models require substantial data and computational resources. Moreover, they often operate as “black boxes,” making it hard to interpret their predictions. Hence, future research should aim to tackle these challenges and further investigate the potential of deep learning in this domain.

4.2. SVM

SVM is a powerful supervised learning algorithm widely used in classification and regression tasks. In the context of wireless channel modeling, SVM can be employed to predict the channel characteristics based on input features [11]. The main idea behind SVM is to find an optimal hyperplane that maximally separates different classes or regression targets.

1. Feature Extraction Before applying SVM, appropriate features need to be extracted from the wireless channel data. These features can include statistical parameters, such as mean, variance, and higher-order moments, as well as spectral characteristics, such as power spectral density and autocorrelation. Feature extraction plays a vital role in capturing the relevant information from the wireless channel data.

2. Training Phase In the training phase, a labeled dataset is used to train the SVM model. The labeled dataset consists of input feature vectors and corresponding channel characteristics. SVM learns the optimal hyperplane by maximizing the margin between different classes or regression targets [12]. The choice of the kernel function, which defines the similarity measure between feature vectors, is crucial in SVM. Commonly used kernel functions include linear, polynomial, and radial basis function (RBF).

Testing and Evaluation After training, the SVM model can be applied to new, unseen data to predict the wireless channel characteristics. The performance of the model can be evaluated using various metrics, such as mean squared error (MSE) for regression tasks or accuracy, precision, and recall for classification tasks. Cross-validation techniques can also be employed to assess the generalization capability of the SVM model.

4.3. Random Forests

Random Forests is another popular ML technique that can be utilized for wireless channel modeling. It is an ensemble learning method that combines multiple decision trees to make predictions. Random Forests have shown excellent performance in various applications due to their ability to handle complex and high-dimensional data.

Decision Trees At the core of Random Forests are decision trees, which are binary tree-like structures that recursively split the input data based on certain features. Each internal node represents a feature and a splitting criterion, while each leaf node corresponds to a class or regression value. Decision trees are constructed by iteratively selecting the best feature and splitting criterion that maximize the information gain or decrease the impurity measure.

Ensemble Learning Random Forests combine multiple decision trees to make predictions. Each decision tree is trained on a randomly selected subset of the training data, known as the bootstrap sample. Additionally, at each split, only a random subset of features is considered [13]. This randomness helps to reduce overfitting and improve the generalization capability of the model. The final prediction is obtained by aggregating the predictions of individual trees, either through majority voting for classification or averaging for regression.

Feature Importance Random Forests provide a measure of feature importance, indicating the contribution of each feature in the prediction process. This information can be valuable in understanding the underlying characteristics of the wireless channel. By analyzing feature importance, we can identify the most relevant features that affect the channel behavior and potentially optimize the system design.

5. Conclusion

This paper has delved into the transformative role of ML in enhancing wireless channel modeling, marking a significant shift from traditional empirical and deterministic methods. Techniques lik SVM, random forests, and deep learning have been pivotal in optimizing wireless transmission and interpreting complex channel data, from locations to movement patterns over time. Particularly noteworthy is the advent of federated learning, which harmonizes data from numerous devices while safeguarding privacy.

This study’s primary limitation is the reliance on data quality and quantity for ML models in wireless channel modeling. Inconsistent or biased data can significantly impact model performance. Additionally, the computational demands of complex ML algorithms, particularly in real-time applications, pose challenges in resource allocation and energy consumption. The ‘black box’ nature of many ML algorithms also raises concerns about interpretability, making it difficult to understand their decision processes. Furthermore, the rapid evolution of wireless technologies necessitates continuous updates to ML models, adding to their complexity and resource requirements.

Looking ahead, the future of ML in wireless channel modeling is brimming with potential, yet it demands focused research and development. Key areas include improving data dynamics through enhanced availability and real-time processing, and augmenting the interpretability of complex ML models for broader adoption and trust. Developing robust and scalable algorithms that can keep pace with the dynamic nature of wireless networks is essential. The integration of emerging technologies, such as quantum computing, could significantly advance computational capabilities. Emphasizing energy efficiency in algorithms is crucial for their sustainability in large-scale network applications. Lastly, the exploration of innovative modeling techniques and new data sources is vital for improving the accuracy and reliability of ML predictions. These advancements will pave the way for more intelligent, efficient, and reliable wireless networks.

In summary, while ML has opened new avenues in wireless channel modeling, its journey is characterized by continuous evolution and refinement. The future holds the promise of more advanced wireless networks shaped by the advancements in ML, but realizing this potential will require dedicated and innovative research efforts.

Acknowledgement

All the authors contributed equally to this work and should be considered as co-first author.

References

[1] S. M. Aldossari and K. -C. Chen, “Machine learning for wireless communication channel modeling: An overview,” Wireless Personal Communications, vol. 106, pp. 41-70, 2019.

[2] F. Lara et al., “Modeling Wireless Propagation Channel: A Traditional Versus Machine Learning Approach,” XV Multidisciplinary International Congress on Science and Technology, Cham: Springer International Publishing, 2021.

[3] K. A. Akpado, O. S. Oguejiofor, A. Adewale, and A. C. Ejiofor, “Pathloss Prediction for a typical mobil communication system in Nigeria using empirical models,” IRACST-Int. J. Comput. Netw. Wirel. Commun. (IJCNWC), vol. 3, pp. 207-211, 2013.

[4] W. Khawaja, O. Ozdemir, and I. Guvenc, “UAV air-to-ground channel characterization for mmWave systems,” in Proc. IEEE Veh. Technol. Conf. (VTC-Fall), pp. 1–5, Sep. 2017.

[5] M. Lecci et al., “Simplified ray tracing for the millimeter wave channel: A performance evaluation,” in Proc. Inf. Theory Appl. Workshop (ITA), pp. 1–6, Feb, 2020.

[6] Z. Shi, P. Xia, Z. Gao, L. Huang, and C. Chen, “Modeling of wireless channel between UAV and vessel using the FDTD method,” in Proc. WiCOM , pp. 100–104, Sep. 2014.

[7] T. Hu, Y. Huang, Q. Zhu, and Q. Wu, “Channel estimation enhancement with generative adversarial networks.” IEEE Transactions on Cognitive Communications and Networking, vol. 7.1, pp. 145-156, July 2020.

[8] C. Zhang, P. Patras, and H. Haddadi, “Deep learning in mobile and wireless networking: A survey,” IEEE Commun. Surveys Tuts., vol. 21, no. 3, pp. 2224–2287, 2019.

[9] V. Rajat, C. Gangal, M. Sharique, and M. Ansari “Deep Learning based Wireless Channel Prediction: 5G Scenario.” Procedia Computer Science, vol. 218, pp. 2626-2635, 2023.

[10] M. Chen, U. Challita, W. Saad, C. Yin, and M. Debbah, “ML for wireless networks with artificial intelligence: A tutorial on neural networks,” CoRR, vol. abs/1710.02913, 2017.

[11] H. He, C. Wen, S. Jin and G. Y. Li, “Deep learning-based channel estimation for beamspace mmWave massive MIMO systems,” IEEE Wireless Commun. Lett., vol. 7, no. 5, pp. 852-855, Oct. 2018.

[12] A. Alkhateeb, S. Alex, P. Varkey, Y. Li, Q. Qu, and D. Tujkovic, “Deep learning coordinated beamforming for highly-mobile millimeter wave systems,” IEEE Access, vol. 6, pp. 37328–37348, 2018.

[13] Mark A. Graham, Ayalvadi J. Ganesh, Robert J. Piechocki “Low Latency Allcast Over Broadcast Erasure Channels“. pp. 2023