Overcoming Wireless Channel modeling and Relay Signal Selection Via Artificial Intelligence Techniques in the 5G and Beyond

Saud Alhajaj Aldossari
Dept. of Electrical and Computer Engineering
Prince Sattam bin Abdulaziz University
Wadi Aldawsar, Ar Riyadh, Saudi Arabia
S.alhajaj@psau.edu.sa

Abdullah Aldosary
Dept. of Electrical and Computer Engineering
Prince Sattam bin Abdulaziz University
As Sulayyail, Saudi Arabia
ab.aldosary@psau.edu.sa

Kwang-Cheng Chen
University of South Florida
Tampa, Florida 33620 USA
kwangcheng@usf.edu

***Abstract*—Wireless technology has faced technical challenges that have been unresolved or only partially addressed. Issues such as modeling the wireless channel and selecting the optimum signal This paper proposes using Artificial Intelligence (AI) to tackle these concerns. Machine Learning (ML) can estimate wireless channel states based on available data. Regression and classification techniques have been used to improve communication and meet 5G standards. The effectiveness of ML and Deep Learning techniques were compared to achieve the best accuracy. This paper shows how AI can revolutionize the design of 5G-NR and future generations with an accurate prediction of 99.99%.**

***Index Terms*—Machine Learning, Wireless Communications, MmWave, Neural Network, Multilayer Perceptrons, Classification, SVM and Logistic Regression.**

I. Introduction

MACHINE Learning methods are used to develop alternative procedures to enhance the wireless communications of different applications in the 5G era to reach the 3GPP requirements [1]. In this manuscript, two wireless communications issues will be investigated to ensure the AI technique's capability to overcome them. The issues are the complexity of modeling the wireless channel modeling. The classical approaches either by applying empirical or deterministic approaches. The deterministic methods are based on theories such as ray tracing, Maxwell equations and others [2]. While the stochastic is based on empirical measurement models such as Okumura–Hata [3] and COST 231 [4]. The path loss models are estimated based on varieties of factors such as the transmitted signal power, distance, frequency, antenna high, etc. For every environment, there must be a unique model that estimates the attenuated strength of the signal [5]. Channel modeling is the process of incorporating wireless channel parameters into a model that has the capability of forecasting and making a prediction. The propagated electromagnetic waves usually face the surrounding environments that cause the signal to be reflected, diffracted, or propagated through the medium that leads to multipath components and selecting the optimum signal is the second issue in this work [6] [7].

Investigating and overcoming these concerns are based on applying AI techniques that show great results as shown in selection 2. Millimeter-wave provides an alternative frequency band of wide bandwidth to recognize pillar technologies. These requirements were introduced by International Telecommunication Union (ITU) to provide ultra-reliable low-latency communication (URLLC), machine-type communication (mMTC), and enhanced mobile broadband (eMBB) to the 5G applications [8]. The wireless channel modeling is unstable and these effective signals degregate the wireless communications and cause fading, interference, and other wireless issues. Current research topics of propagation signal are dealing with applying AI to estimate the signal strength such as [9] and other such [10] which worked on modeling path loss for urban scenarios based on 3D-convolutional neural networks. Furthermore, the usage of applying AI towards interior communication to predict the path loss was conducted in [13] [12]. With the large amournt of bands in MmWave, [13] used AI algorithms to predict the wireless bands.

Wireless channel modeling is the middleman between the transmitter and the receiver in wireless communication systems. Knowing and learning the propagation environments channel require either deterministic or stochastic methods such as the ray tracing or the empirical method which are complex and inaccurate [14]. Moreover, both these methods are time-consuming and every scenario has to be measured and there must be a way to compromise them to meet the 5G-NR requirements. It's time to adopt and apply machine learning techniques towards the wireless communication issues.

The first issue to be investigated here is, how to reduce the complexity and other cons in the classical wireless channel modeling. ML techniques have been used to investigate this issue where the regression method is used to predict the path loss model instead of the classical approaches. Details of the regression method will be shown next section. The second issue here is relay stations to assist the coverage of base stations in the radio access network (RAN) emerge as an attractive technique in the MmWave frequency band. However, relay link selection to handover the signal usually based on the strongest link becomes a critical technology to facilitate RAN using MmWave. Neural network algorithms exhibit a procedure to assist the base station to select the optimum received signal or make a decision to perform the handover.

The components of this journey are arranged as follows. Section 2 exhibits a literature review of wireless channel modeling, while Section 3 presents the methodology for data acquisition and model development. Results and discussion are presented in in the same section while the conclusion is in Section 4.

II. Wireless Channel Modeling

A fundamental design of a wireless communication system is radio frequency channel modeling. The state of the art of channel modeling is defined as a fundamental part of the physical layer in communication systems that can be represented by mathematical parameters to model the channel. The wireless channel is the transmission medium for mobile communications which is the process of involving wireless channel parameters in a model that has the capability of forecasting and making a prediction. [15] have proposed an Extreme Learning Machine (ELM) algorithm to predict the path loss model for lower microwave frequency of an outdoor scenario to modify the base station deployment. The propagated signals face an issue with the surrounding environment that case the signals to be either destructive or constructive during the propagation. During the past decade, deterministic and empirical methods were performed to measure the amount of degradation of the transmitted signal and that is still considered as a drawback, especially with the requirement of the 5G- new radio.

The first issue that would be investigated in this manuscript is the complexity of conducting measurement campaigns in every single scenario is time-consuming and inaccurate. The classical procedure to come up with a wireless channel model is to establish a new measurement campaign for every environment such as urban, rural, suburban, and others. Instead of measuring every single field to obtain a path loss model, regression methods can be used to estimate a path loss model from a specific field. An example, building a new wireless channel modeling for an urban environment requires performing a measurement campaign to collect data to build the model. While with machine learning regression techniques, that urban model can be estimated if we have any previous data from different environments. Meaning, having a single environment dataset can be used to create a new model of different environments. This method will reduce the complexity and reduce the time and the amount of money [16].

Millimetre-wave supplies an alternative frequency band of wide bandwidth to better realize pillar technologies for 5G - new radio (5G-NR). When using the MmWave frequency band, relay stations to assist the coverage of base stations in the radio access network (RAN) emerge as an attractive technique. However, relay selection to result in the strongest link becomes the critical technology to facilitate RAN using MmWave. An alternative approach toward relay link selection is to take advantage of existing operating data and apply appropriate artificial neural networks (ANN) and other machine learning algorithms to alleviate severe fading in the MmWave band. In this paper, we apply classification techniques using ANN with multilayer perception to predict the path loss of multiple transmitted links based on a certain loss level, and thus execute effective relay selection, which also recommends the handover to an appropriate path. ANN with multilayer perception is compared with other ML algorithms to demonstrate effectiveness for relay selection in 5G-NR.

III. Results

In this section, both regression and classification techniques will be used to investigate wireless channel modeling. Where the regression approach will be applied to assure the capability to predict a certain wireless environment based on a dataset from a different environment. Three methods of regression techniques will be used to overcome the complexity of the wireless channel modeling. These methods are linear, multiple linear, and Support Vector Machines Regression. While classification approach will be used to classify the propagated signals to accelerate the base station decision to select the optimum received signal. In this approach, deep learning and machine learning techniques will be performed and compared to enhance the accuracy of the prediction.

A. Linear and Multiple linear Regression

The classic wireless communication channel modeling is performed using Deterministic and Stochastic channel methodologies. Nowadays, machine learning (ML) emerges to revolutionize system design for 5G and beyond. ML techniques such as supervised learning methods will be used to predict the wireless channel path loss of a variety of environments based on a certain dataset. The propagation signal of communication systems fundamentals is focusing on channel modeling, particularly for new frequency bands such as mmWave. Machine learning algorithms can facilitate rapid channel modeling for 5G and beyond systems such as cellular and Vehicle to Vehicle (V2V) communications systems due to the emerging of wireless big data. When irregularity of the wireless channels leads to a complex methodology to achieve accurate models, machine learning algorithms explore to reduce the complexity and increase the accuracy that reduces the number of measurements. In this paper, we demonstrate applying machine learning to develop alternative procedures to enhance the path loss models using machine learning techniques. Due to channel complexity and the time consuming the measurements take, this journey develops alternative procedures to reduce the channel measurements that are used to predict path loss models. This can be done by using the measurement of a certain measurement scenario to predict and assist in the prediction of the path loss model of a different environment.

Estimating the path loss model such as the floating model as (1) can be taken to the form of regression whereas linear regression has only one channel feature which is distance. While multiple linear regression consists of many parameters that represent different wireless channel features such as delay, receive signal strength, distance, and others.

Floating-Intercept (FI) Model is a path loss model and can be estimated using the regression method as shown:

$$PL^{FI}(f,d)[dB] = \alpha + 10\beta log_{10}(d) + X_{\sigma}^{FL} \tag{1}$$

$$\hat{Y} = \hat{\beta}_0 + \sum_{i=1}^{k} \hat{\beta}_i X_i \tag{2}$$

$$E(\beta_0, \beta_i) = \sum_{i=1}^{p} [y_i - (\beta_0 + \beta_i X_i)]^2 \tag{3}$$

Equation 2 is a multiple linear equation to estimate output which is in our case the path loss. While equation 3 is used to predict the parameters. By applying this approach to estimate the coefficient parameters and then characterizing the theoretical loss L is obtained.

$$\arg\min_{j} L = \frac{1}{N} \sum (\hat{Y}(k) - Y(k))^2 \tag{4}$$

B. Support Vector Machines Regression

Support Vector Machines (SVM) is another method of the supervised ML algorithms that can be used in either regression or classification [17]. In this section, SVM is used to fit the data in terms of regression based on a theoretical foundation based on Vapnik-Chervonenkis's theory to minimize the error. SVM is a type of supervised learning to perform a classification task that was presented by [18] and the basic idea of SVM is to map a dataset from a finite-dimensional space to a high-dimensional space in the form of linear and nonlinear shapes. The extension of that technique is support vector regression which is used in regression techniques in a continuous case.

$$f(x, w) = \sum_{j=1}^{m} wx + b \tag{5}$$

SVR is a regression method that can be used for wireless channel modeling and it's different from SVM. The output of the algorithm supposes to be continuous values instead of Classification which is categorical. The function that will be used to describe this method is called kernel and is used to map lower dimensional data into higher dimensional data. It's well known that SVR uses a hyperplane to predict the response instead of using it as a separation line in the SVM to distinguish the classes. An advantage of applying SVR is the absence of the local minima to and used instead of the margins [19].

SVR is different than regular linear regression by fitting the error within a certain threshold instead of minimizing the error using the least square error. Furthermore, the fitting line in the SVR is based on the maximum data points within certain boundaries.

$$wx + b = 0d \tag{6}$$

While the boundaries are shown as

$$-\epsilon \leq y - wx - b \leq \epsilon \tag{7}$$

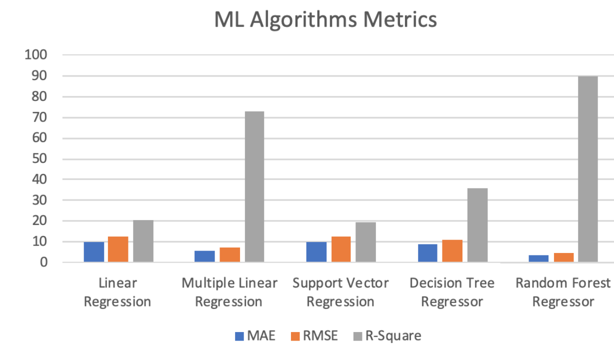
where ϵ is the error of the data point to each boundary.

$$e_i^2 = \arg min \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 \tag{8}$$

Figure 1 shows the path loss prediction and the results of the accurate estimation can be presented by R-Square using equation 9.

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \overline{y_i})^2}, \tag{9}$$

where y_i, $\hat{y}_i$, and $\overline{y_i}$ represent the actual, predicted, and mean values, respectively, in the prediction of the path loss, PL.



??

Fig 1: Regression techniques that are used to predict path loss using different environment's data.

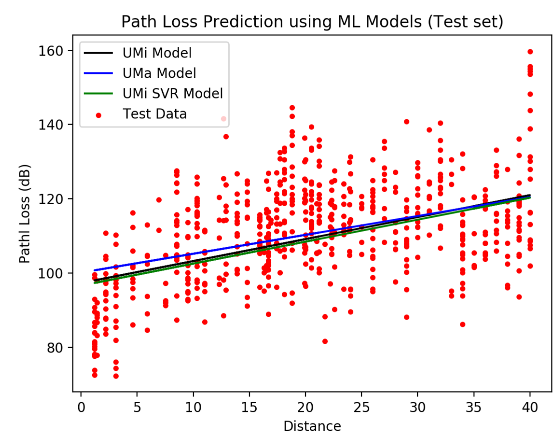


Fig 2: ML Regression fitting line techniques.

Figure 2 shows three models, the red dots are simulated data from the MUi environment and the black model is the urban micro-cell (UMi) model. The blue line is an urban macro model which can be seen in how close the model is with an R-square of 0.21 for UMi and 0.53 for UMa which considers a great result. While the green regression line is linear SVR.

Conveniently, this procedure helps with reducing the time consumed to collect several measurements in terms of modeling the wireless channel modeling, enhancing accuracy and reliability. Solving these issues can be applied to other applications such as vehicle-to-vehicle (V2V), IoT, and other networking utilization. Determining and solving this issue meet the 5G-NR pillars technologies of enhancing mobile broadband (eMBB) and ultra-reliable and low-latency communication (uRLLC) and massive machine type communications (mMTC).

The loss of the SVM can be obtained using the below formula

$$\mathcal{L}_\epsilon(y, f(x,w)) = \begin{cases} 0 & \text{if } |y - f(x,w)| \leq \epsilon, \\ y(x) - f(x,w) - \epsilon & \text{o.w..} \end{cases} \tag{10}$$

C. Neural Networks Algorithms

Neural networks work as the human brain's neurons and the difference between ANN and the human brain is the p4ess of electro-chemical, while ANNs are managed by electro-mechanical signals. ANN techniques have not reached human efficiency due to multiple reasons such as the number of human brain neurons much higher than the number of artificial neural networks. The ANNs algorithms have the capability to learn the interference between the data and map the training data to the label output as supervised learning [20]. Moreover, ANN can infer the relation between the channel parameters in a regression, classification, and recognition problem [21]. Applying ANN methods to wireless communications issues can enhance the performance such as overcoming the handover issue since ANN is capable of adapting its structure during the learning computing. ANN techniques such as Multilayer Perceptrons (MLP) algorithm can improve the process more than other classification methods in the previous section. Multilayer Perceptrons follow the form as shown below.

$$y = f(\sum_{i=1}^{n} W_i X_i + b_i) \tag{11}$$

Where f is the non-linear activation function and W is the vector of weights of X vector inputs and b is the error. In this work, we proposed six models of Multilayer Perceptrons with different specifications following the pseudocode procedure. By comparing the ANN methods to other machine learning techniques, we can see that ANN algorithms performed better than others and that can be seen in the below figures that are based on Receiver Operating Curve (ROC) and Precision-Recall Curves (PRC) The ROC curve presents the trade-off between the true positive rate and the false positive rate to evaluate prediction performance [22] as follows.

Involving ROC metrics requires the need of two parameters which are sensitivity (true positive rate) and specificity (true negative rate) as shown below.

$$sensitivity = \frac{TP}{TP + FN} \tag{12}$$

$$specificity = \frac{TN}{TN + FP} \tag{13}$$

However, the PRC curve is based on the relation between precision and Recall.

$$precision = \frac{TP}{TP + FP} \tag{14}$$

$$Recall = \frac{TP}{TP + FN} \tag{15}$$

where the notations are as follows, a true positive (TP), a false positive (FP), a true negative (TN), and a false negative (FN).

Algorithm 1 MLP Feed Forward and Backward Propagation

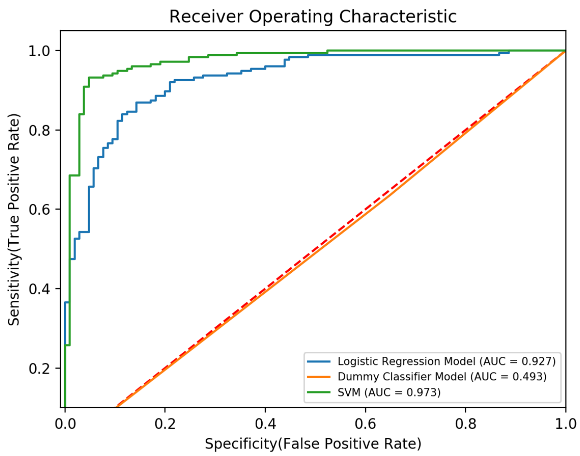
Require: Initialize W_i, b_i and ℓ weights at random, bias variables, and choose a learning rate.
1- Feed $X_(i)$to the input layer.
2- Compute the neurons using summation and then apply an activation function such as the Sigmoid function.
3- If the activation signal pass, feed-forward through networks to produce output(s).
4- Compute the output layer using $Y_i = f(\sum_{i=1}^{n} W_{ij} X_i + b_i)$.
5- Compute the error $e = \sum_{i=0}^{n} \frac{1}{2}(Y_t - Y_i)^2$.
6- Compute back-propagation layer by layer.
7- Update all weights and go back to step 1
8- Keep updating the weights until converges using iterations.

Multiple MLP feedforward models have been used in this work with different specifications as shown below.

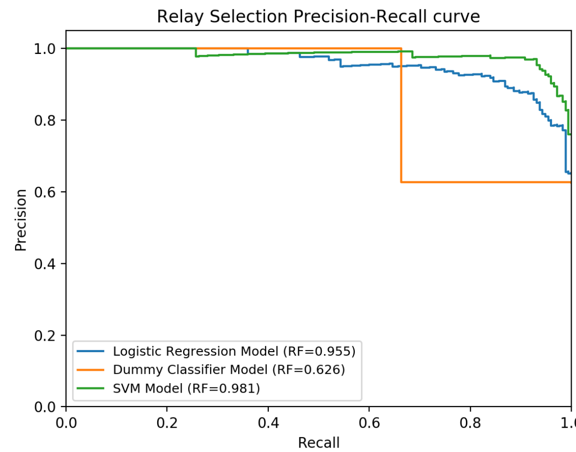
- Model 1: One Hidden Layer of 10 Neurons
- Model 2: Two Hidden Layers of 50 and 10 Neurons
- Model 3: Three Hidden Layers of 10, 50 and 10 Neurons
- Model 4: Four Hidden Layers of 10, 50, 50 and 10 Neurons
- Model 5: Five Hidden Layers of 10, 50, 100, 50 and 10 Neurons
- Model 6: Eight Hidden Layers of 10, 50, 100, 100, 50 and 10 Neurons.

Multilayer Perceptrons neural networks have been compared with machine learning algorithms to predict the optimum propagated link. Figure 3, presents the results and compassion of these algorithms to predict and select the best link. Furthermore, an observation from applying the neural networks to the wireless communications issues, we detected that the number of hidden layers should be lower than the number of inputs by 30%. By applying this observation, model 6, began degrading once the number of hidden layers have achieved 70% of the number of the inputs as can be seen in Figure 5. From the figure, it's obvious that MLP-ANN depends on the number of the network structure such as the number of nodes and layers. The ANN is sensitive to the number of hidden layers and neurons that can cause underfitting and overfitting [23]. Moreover, Other former machine learning algorithms have been compared to our models such as support vector machines that could not outperform well in overcoming the relay link selection.

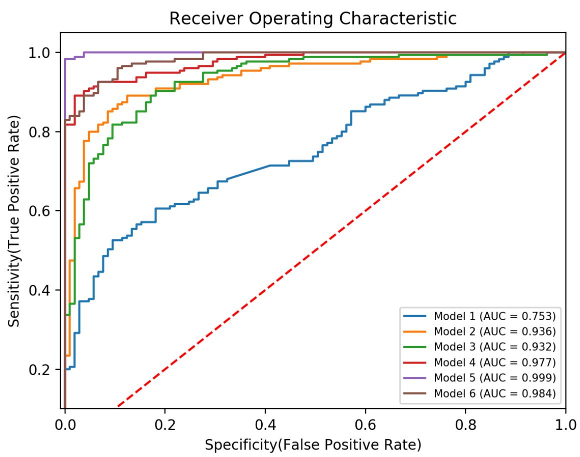
Critical and further topics such as power control, modulation, interference, handover and other classical issue are recommended to be investigated by artificial intelligence.



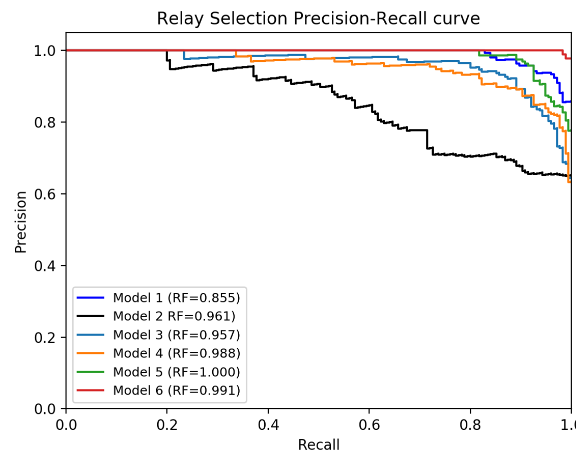
(a) Case I: ROC of ML Technique



(b) Case II: PRC of ML Technique



(c) Case III: ROC of ANN Technique



(d) Case IV: PRC of ANN Technique

Fig. 3: Simulation results for both AI and ML methods.

IV. Conclusion

In this article, multiple AI algorithms have been covered to overcome wireless communications drawbacks in a variety of communication applications such as the wireless system in terms of 5G and beyond. The capability and potential of Machine learning (ML) techniques that have been applied in this journey to meet the 5G-NR. The purpose of this letter elaborates on the ability of machine learning to solve other communications issues. Algorithms such as neural networks have been used as a classification technique to solve the handover issue by selecting the best propagation link based on the path loss. Regression techniques have been used as well to overcome the complexity and time consumption of collected measurements of every single field to build a communication model. Other machine learning techniques are already used such as SVM, and logistic regression to overwhelm other wireless communication problems. We conclude this journey that MLP-ANN acts better in selecting the optimum propagated signal compared to other machine learning techniques to meet third 5G -new radio (NR) requirements such the ultra-reliable and low latency communications.

V. Acknowledgement

This study is supported via funding from Prince Sattam bin Abdulaziz University project number (PSAU/2023/R/1444).

References

[1] Aldossari, Saud Mobark and Chen, Kwang-Cheng, "Predicting the Path Loss of Wireless Channel Models Using Machine Learning Techniques in MmWave Urban Communications," - *Accepted to be appeared in the 22ND International Symposium on Wireless Personal Multimedia Communications*, Lisboa, Portugal, 24-27 November 2019; pp.1-5.

[2] Mohtashami, V. & Shishegar, A. Modified wavefront decomposition method for fast and accurate ray-tracing simulation. *IET Microwaves, Antennas and Propagation*. **6**, 295-304 (2012)

[3] Hata, M. (1980). Empirical formula for propagation loss in land mobile radio services. IEEE Trans- actions on Vehicular Technology, 29, 317–325.

[4] Erceg, V., Greenstein, L. J., Tjandra, S. Y., Parkoff, S. R., Gupta, A., Kulic, B., Julius, A. A. and Bianchi, R. (1999). An empirically based path loss model for wireless channels in suburban environments. IEEE Journal on Selected Areas in Communications, 17(7), 1205–1211.

[5] Chiroma, H., Nickolas, P., Faruk, N., Alozie, E., Olayinka, I., Adewole, K., Abdulkarim, A., Oloyede, A., Sowande, O., Garba, S. & Others Large Scale Survey for Radio Propagation in Developing Machine Learning Model for Path Losses in Communication Systems. *Scientific African*. pp. e01550 (2023)

[6] Ericsson. More Than 50 Billion Connected Devices; White Paper; Ericsson: Stockholm, Sweden, 2011.

[7] Sultan, Kashif, Ali, Hazrat and Zhang, Zhongshan., "Big Data Perspective and Challenges in Next Generation Networks. Future Internet". MDPI, 10. 56. 10.3390/fi10070056. 2018.

[8] K.-C. Chen, T. Zhang, R. Gitlin, and G. Fettweis, "Ultra-low latency mobile networking," IEEE Netw., pp. 1–7, Early Access 2019.

[9] Aldossari, S. Predicting Path Loss of an Indoor Environment Using Artificial Intelligence in the 28-GHz Band. *Electronics*. **12** (2023), https://www.mdpi.com/2079-9292/12/3/497

[10] Kim, H.; Jin, W.; Lee, H.. mmWave path loss modeling for urban scenarios based on 3D-convolutional neural networks. In Proceedings of the 2022 International Conference on Information Networking (ICOIN), Republic of Korea, 12–15 January 2022; pp. 441–445.

[11] Aldossari, S. Predicting Path Loss of an Indoor Environment Using Artificial Intelligence in the 28-GHz Band. *Electronics*. **12**, 497 (2023)

[12] Wu, D.; Zhu, G.; Ai, B. Application of artificial neural networks for path loss prediction in railway environments. In Proceedings of the 2010 5th International ICST Conference on Communications and Networking, Beijing, China, 25–27 August 2010; pp. 1–5.

[13] Aldossari, S. Predicting Path Loss of an Indoor Environment Using Artificial Intelligence in the 28-GHz Band. *Electronics*. **12**, 497 (2023)

[14] Nuñez, Y., Lovisolo, L., Silva Mello, L. & Orihuela, C. On the interpretability of machine learning regression for path-loss prediction of millimeter-wave links. *Expert Systems With Applications*. **215** pp. 119324 (2023)

[15] S.I. Popoola, S. Misra, A.A. Atayero, Outdoor Path Loss Predictions Based on Extreme Learning Machine,Wireless PersonalCommunications, pp. 1–20

[16] Aldossari, Saud Mobark and Chen, Kwang-Cheng , "Machine Learning for Wireless Communications Channel Modeling: An Overview," in Wireless Personal Communications, vol. 106, no. 1, pp. 41-70, March 2019. doi: doi.org/10.1007/s11277-019-06275-4

[17] Cengiz, A., Budak, M., YAĞMUR, N. & BALÇIK, F. Comparison between random forest and support vector machine algorithms for LULC classification. *International Journal Of Engineering And Geosciences*. **8**, 1-10 (2023)

[18] K. Sankhe, C. Pradhan, S. Kumar, and G. Ramamurthy, "Machine Learning Based Cooperative Relay Selection in Virtual MIMO," p. 6, Jun. 2015.

[19] V. Kecman, Support Vector Machines: An Introduction. Springer, New York, 2005.

[20] Kurani, A., Doshi, P., Vakharia, A. & Shah, M. A comprehensive comparative study of artificial neural network (ANN) and support vector machines (SVM) on stock forecasting. *Annals Of Data Science*. **10**, 183-208 (2023)

[21] Y. Zhang, ,J.Wen, G.Yang, Z.He, and J.Wang,"Pathlosspredictionbased on machine learning: Principle, method, and data expansion," Appl. Sci., vol. 9, p. 1908, May 2019.

[22] Zaki, A., Métwalli, A., Aly, M. & Badawi, W. Wireless Communication Channel Scenarios: Machine-Learning-Based Identification and Performance Enhancement. *Electronics*. **11**, 3253 (2022)

[23] Mom M.J, Mgbe C.O. and Igwue G.A, Application of Artificial Neural Network for Path Loss Prediction In Urban Macro cellular Environment, American Journal of Engineering Research, 3(2), 2014, 270-27