2022 18th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob) | 978-1-6654-6975-3/22/$31.00 ©2022 IEEE | DOI: 10.1109/WIMOB55322.2022.9941672

Deep Learning-Based QoE Prediction for Streaming Services in Mobile Networks

Gan Huang*, Ozgur Ercetin*, Hakan Gokcesu†‡, Gokhan Kalem‡
*Faculty of Engineering and Natural Sciences, Sabanci University, Istanbul, Turkey; (gan.huang,oercetin)@sabanciuniv.edu
†Department of Electrical and Electronics Engineering, Bilkent University, Ankara, Turkey; (hgokcesu)@ee.bilkent.edu.tr
‡5G Research and Development, Turkcell Technology, Istanbul, Turkey; (gokhan.kalem)@turkcell.com.tr

***Abstract*—Video streaming accounts for the most of the global Internet traffic and providing a high user Quality of Experience (QoE) is considered an essential target for mobile network operators (MNOs). QoE strongly depends on network Quality of Service (QoS) parameters. In this work, we use real-world network traces obtained from a major cellular operator in Turkey to establish a mapping from network side parameters to the user QoE. To this end, we use a model-aided deep learning method for first predicting channel path loss, and then, employ this prediction for predicting video streaming MOS. The experimental results demonstrate that the proposed model-aided deep learning model can guarantee higher prediction accuracy compared to predictions only relying on mathematical models. We also demonstrate that even though a trained model cannot be directly transferred from one geographical area to another, they significantly reduce the volume of required training when used for prediction in a new area.**

***Index Terms*—quality of experience, prediction, deep learning, video streaming, mobile networks, key performance indicators**

I. Introduction

With the rapid development of the wireless multimedia technology, video streaming has become an indispensable part of our lives [1]. Users can watch videos on mobile devices, and are stimulated with unique requirements in expecting ultra-high-definition quality [2]. Several factors further fuel the wide adoption of new and improved data services: a continuous evolution of the range of applications, increased users' awareness and the constantly evolving performance of wireless networks [3]. Wireless multimedia systems are being developed to download videos faster, improve live video streaming quality and make strong connections between cell towers and user equipment [4]. Nowadays, machine learning and deep learning tools are adopted to improve the performance of wireless multimedia systems [5]. Accordingly, this improvement can be realized by the wireless multimedia systems by benefiting from the exploration of precious details about users' behavior, content information, and network dynamics [6]. There are two important categories of performance metrics for modern communication networks to consider: QoE and QoS [7]. User Quality of Experience (QoE) has been the most important performance criterion in modern communications networks [8]. Unlike Quality of Service (QoS), which describes network performance, user QoE depends not only on the network but also on the content, user preferences, and how the content is delivered. In many services, e.g. video streaming, user QoE is measured as Mean Opinion Score (MOS). Although QoE is a subjective measure, some data-driven objective QoE evaluation approaches have been proposed such as ITU P.1203 [9]. The mean opinion score is based on objective parameters such as video resolution, video startup delay time, etc. In this work, we have drive test data taken from different locations and times which supplement such information. Our algorithm is aimed to make predictions with virtual drive tests following real world deployment. The data from traditional drive tests are inefficient when compared to virtual drive tests, hence their need is minimized. The datasets under our investigation can also be appealing for machine learning applications such as throughput prediction or RSRP prediction.

The rest of the paper is organized as follows. Section II reviews the related works of the path loss prediction and QoE prediction. Section III explains the methodologies, including data analysis and model-aided deep learning method for path loss and QoE prediction. Section IV describes our measurement setup provided for data analysis, and the background information about the available individual KPIs are presented. Section V proposes our approach for the model-aided deep learning method for path loss and QoE prediction. Section VI gives our results and discussions. Section VII presents the conclusion and future work.

II. Related Works

A. Path Loss Prediction

The modeling and prediction of path loss in wireless communications have been an active area of research. The authors in [10] used artificial neural network (ANN) models for macrocell path-loss prediction. In constructing the ANN model, different-sized ANNs were trained by using different backpropagation training algorithms, such as gradient descent and Levenberg–Marquardt. Reference [11] proposed a path loss prediction combining four machine learning algorithm, including back propagation neural network (BPNN), support vector regression (SVR), random forest, and AdaBoost. To ensure the accuracy of prediction, the empirical model and machine-learning-based model were all considered. [12] proposed an improved path loss prediction model for mobile communications systems using deep learning algorithm by

This work is supported in part by Tübitak under grant number 119E198.
H. Gokcesu is supported in part by Turkcell Technology within the framework of 5G and Beyond Joint Graduate Support Programme coordinated by Information and Communication Technologies Authority.

collecting satellite imagery and position indicator. Due to the increase in data, the proposed approach was capable of improving the accuracy of path loss prediction. A machine learning architecture for predicting path loss by considering a combination of three key techniques: artificial neural network (ANN)-based multi-dimensional regression, Gaussian process-based variance analysis, and principle component analysis (PCA)-aided feature selection was proposed in [13]. PCA was applied to decrease the number of features in the collected dataset and make the learning model less complex. Then, ANN learned the path loss model from the simplified dataset by reducing the dimension, and Gaussian process was used for the shadowing effect. In [14], multilayer perceptron (MLP) neural network in artificial neural network (ANN) was utilized to accurately do the prediction of path loss for wireless communication networks, in which the impact of environmental features, ANN architectures, the dimension and percentage of training samples on PL prediction models were considered for model validation.

B. QoE Prediction

Recently, the prediction of the user QoE in mobile networks has also been a hot area of research. [15] proposed a new context-aware QoE prediction model, in which Bayesian Networks and Utility Theory were applied to do QoE inference under uncertainty. Authors in [16] presented a deep learning-based MOS prediction approach with a large-scale QoE dataset in mobile video transmission. Through collecting users' scores for four metrics, including visual quality, loading, stalling, and overall quality, and 89 network parameters, a deep learning model was developed to build the relationship between network parameters and the subjective QoE values after feature selection and data cleaning. [17] formulated a Bayesian network based on a probabilistic graphical model to predict QoE of video streaming performance in non-real-time. In [18] a flexible QoE prediction model was designed to do the anomaly detection in adaptive video streaming, including predictor and anomaly detector. Long Short Term Memory (LSTM) Recurrent Neural Networks (RNNs) was used to perform the prediction of QoE in consideration of network and application Key Performance Indicators (KPIs). In [19], to improve QoE for users in the Long-term evolution (LTE) network, a deep learning approach based on the evaluation of a mean opinion score (MOS) for a real-time video conference service for optimal handover time prediction was proposed.

III. Methodology

A. Data Analysis

Datasets are collected by conducting drive-tests in ten different locations in Turkey. The drive-test vehicle collects both RF measurements and video quality data while streaming a finite-length video named "Big Buck Bunny" from the YouTube servers. This video is chosen by most of the QoE measurement software due to its inherent characteristics. The measurements are limited to fixed length duration of 60 seconds, and the video streaming is stopped at the end of this duration. Video QoE is measured by a software called PEVQS which is well-known and widely used by operators worldwide. The software outputs a value between 1 and 5, every 5 seconds, commonly referred to as Mean Opinion Score (MOS) in reference to the averaging of scores given by the participants in a subjective test. However, unlike a subjective test, this calculated MOS is an objective calculation based on the KPIs of the video measured by the software. The parameters measured by the software are unknown to our analysis. Additionally, the channel KPIs are measured and recorded every second, allowing us to build a correlation between MOS and radio KPIs. Channel KPIs include Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), Signal-to-Interference plus Noise Ratio (SINR), Physical Resource Block (PRB) utilization of Physical Downlink Shared CHannel (PDSCH), PRB utilization of Physical Uplink Shared CHannel(PUSCH), DownLink PRB Utilization (DL_PRB_UTILIZATION), DownLink Throughput (APP_DL_THROUGHPUT), UpLink Throughput (APP_UL_THROUGHPUT). Finally, in different locations the manufacturers of cell towers are also different, and the data is collected mostly from dense-urban environments.

B. Deep Learning Method for Path Loss and QoE Prediction

The closest work to ours is [12], which also proposed a *model-aided deep learning method for path loss prediction* albeit under different specifications. Note that the path loss prediction has always been of vital importance in communication networks. There are several empirical path loss models for this purpose. For example, in greenfield implementations, simple empirical loss models are used. In urban environments where coverage already exists, the distribution and management of interference increases in complexity, so more advanced channel models are required. The power-distance relationships in current empirical models describe specific local geostatistics that influence signal quality parameters. The use of empirical models usually results in *over-* or *under-* prediction of signal quality parameters and requires additional calibration. Therefore, accurate channel models are still in need to evaluate future generation mobile communication systems. Channel models have general requirements and should consider a wide selection of propagation scenarios to limit the need to calibrate through extensive measurements. Furthermore, cognitive networking is considered as a necessary part of future solutions. Note that cognitive networking is expected to have tight needs on channel models, not solely in terms of accuracy but conjointly in terms of computational performance. Thus, new channel models offering improvements in both aspects are of great interest.

The primary focus of our work is predicting the mean received power under slow fading impairments such as shadowing. We aim to improve channel models for modeling the coverage not only in terms of signal strengths but from video streaming QoE perspective. For that aim, we utilize data driven (adaptive) approaches based on deep learning.

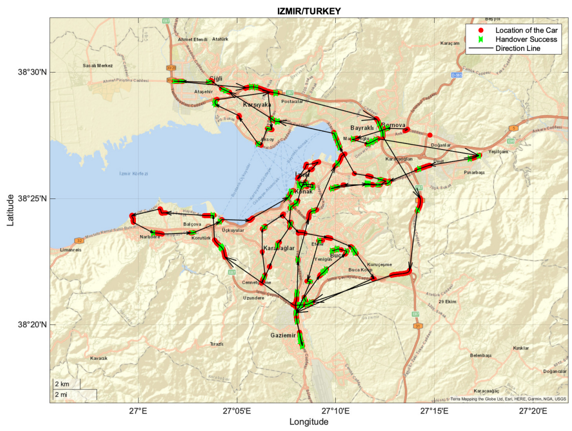


Fig. 1: Road traveled for data collection in Izmir, Turkey. Points represent measurements (red) and handovers (green).

IV. The Dataset: Key Parameter Indicators

A. *Measurement Setup*

Due to limited space, in the following, we will only discuss the dataset collected from Izmir. Our deep learning methods will be tested on two other locations in the subsequent sections. The drive-tests relating to the data in this section conducted nonstatic outdoor measurements between 08:43 on 16 February 2021 and 17:25 on 16 February 2021 in a car (the measuring user equipment was inside of the car) traveling over the route through Izmir, Turkey as depicted in Fig.1. The measurements are made with a smartphone (Samsung S8) in an operational LTE network of one of the Turkish MNOs. The smartphone was connected to the nearest cell tower, named as the primary cell in our dataset. If it loses that connection, then it tries to connect with other stations whose names are Secondary Cell 1 (S1) and Secondary Cell 2 (S2).

B. *Cell-Specific Reference Signal*

We depict the measurements in our dataset collected from the city of Izmir in Fig.2 with respect to time. Note that due to lack of space, we only show a small portion of parameters within the dataset: Reference Signal Received Power (RSRP), and Signal-to-Interference plus Noise Ratio (SINR) as the main parameters for radio signal performance and Mean Opinion Score (MOS) as the indicator for user QoE. Note that RSRP is the average power received from a single reference signal and its general range is from -44 dBm (good) to -140 dBm (bad). RSRP takes the reference point as a UE's antenna connector. RSRP can be defined as the linear average of the power contributions of the resource elements carrying cell-specific reference signals in the frequency band considered for measurement. SINR is the reference value used in system simulation, which is a hallmark that is normally used to measure network quality. However, it should be noted that SINR is not specified by 3GPP and therefore UEs do not report SINR to networks. SINR is measured internally

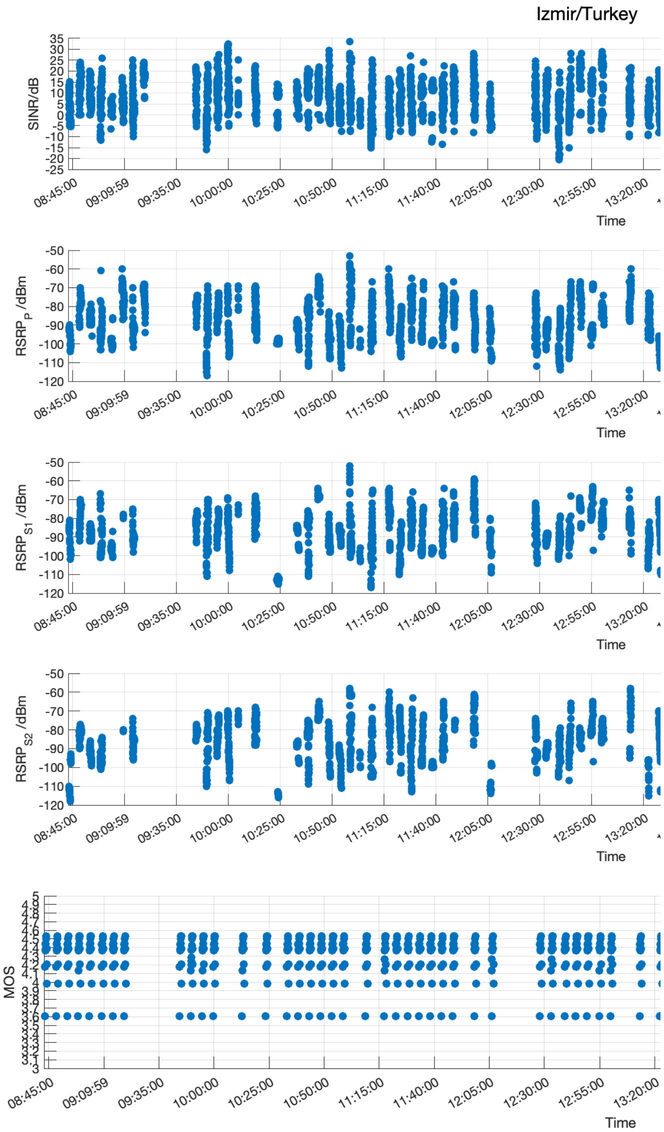


Fig. 2: SINR, RSRP, MOS vs. time in Izmir-Turkey dataset. Cell subscripts: P (primary), $S1$, $S2$ (secondary one, two).

by UEs and recorded for use by testing tools. In Fig.2, the measurement points appear to reside in a vertical line, since each measurement *session* spans a length of approximately 60 seconds. We also note that within this period, radio parameters vary significantly due to the mobility of the test vehicle. Additionally, when the MOS measurements are observed a clear pattern is recognized. MOS starts low but increases within a session as time progresses due to buffering by the video client at the receiver. In fact, this pattern will be used by our deep learning model to accurately predict the MOS values. The similarity with the role of distance for path loss is recognizable, as the start of a session is the furthest point from the stability, and thus the inverse of time acts a distance.

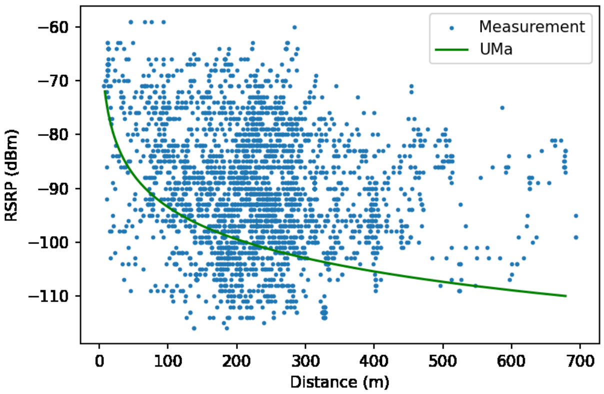


Fig. 3: Experimental measurement of RSRP for the 2600 MHz channel as a function of distance.

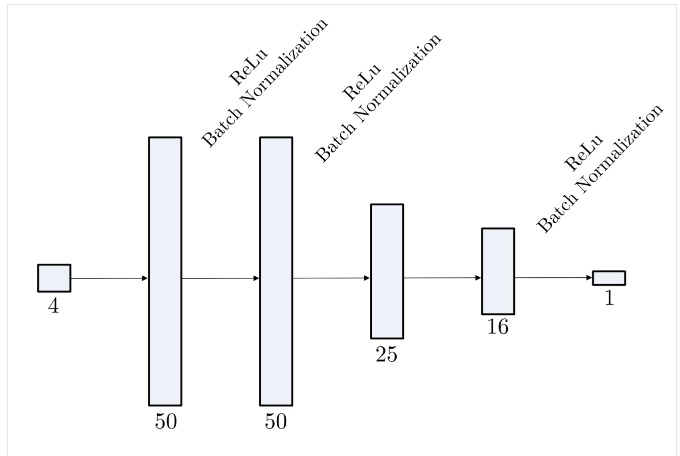


Fig. 4: Deep learning model.

C. Mean Opinion Score

Mean Opinion Score is a numerical measure of the quality of video sessions in telecommunications. It is a human-decided quality. It is generally judged between 1 (poor quality) and 5 (excellent). In practice, it is often used to judge numerical approximations of global phenomena. As shown in Fig.2, in our dataset, the values of MOS are observed to vary approximately between 3.6 and 4.6.

V. Model-Aided Deep Learning Method to Use in Path Loss and QoE Prediction

In this section, we employ a deep learning (DL) approach to augment a simple but contemporary path loss model to facilitate the learning of channel conditions and video streaming QoE based on user locations.

A. Path Loss Prediction

Model-based methods are the standard approach for accounting for radio propagation effects in network simulation and planning. Existing channel models, for example, 3GPP TR 38.901 [20], which is employed to train our deep learning algorithm, can provide high computational efficiency and allow comparison of different methods in a highly controlled environment. These methods are mainly capable of imitating the complex features of the real world radio propagation. Model-aided artificial intelligence methods make it possible to optimize the accuracy of the predicted models and to further reduce the number of necessary training samples. With the advances in modern deep machine learning methods, the mathematical radio propagation models traditionally used in wireless communications are being replaced and/or improved by models trained with large amounts of real world data. Among the most recent mathematical propagation models one can refer to, UMa-B (defined in TR 38.901 by 3GPP) is suitable for urban environments. In UMa-B model, the height of the cell tower (the transmitter), the height of the vehicle (the receiver), and carrier frequency information are the main input parameters. Nevertheless, mathematical models are inadequate in predicting path loss in the contemporary urban environments as demonstrated in Fig. 3, where the blue dots represent real measurements of RSRP, and the green line represents the RSRP calculated by UMA-B model [1].

The idea of introducing a residual path loss into the proposed model leads to an increased performance, which is observed in training the model through the data. The deep learning model employs a simple path loss model for assisting the learning process. More specifically, we define the output of the simple path loss model as an estimated link budget. In the proposed deep learning model, the input to the model is as follows: $x_n = [lat, lon, d]$ where (lat, lon) are the geographical coordinates of the receiver and d is the distance between the transmitter and the receiver. In our datasets, we do not have the exact distance information between the cell tower and the car, and which cell tower is connected to the receiver. Hence, in the analyses, we assumed that the receiver is always connected to the nearest cell tower [2]. A deep machine learning model is implemented to learn a correction of the estimated path loss produced by the simple path loss model. We define $y(x_n, w, \theta) = z([x_n, L(d)], w, \theta) + L(d)$. Our aim is to obtain a regression model that predicts the RSRP continuously. Hence, the model is formalized as follows: $t_n = y(x_n, w, \theta) + \epsilon$, where y is the function to learn, x_n is the input, w are the weights, θ are the hyper-parameters and ϵ is Gaussian distributed noise and the observation t_n is the resultant RSRP. The deep learning model is summarized in Fig. 4. For training, data is shuffled first and split between %10 test and %90 train. The batch normalization is used with batch size taken as 100. The model is learned over 100 epochs: with ReLU as the activation function, 1e-2 as the learning rate, Mean Squared Error as the loss, and Adam as the optimizer.

[1] The cell tower height is 40 meters, the height of the car is 1 meter and the carrier frequency is 2600 MHz.

[2] Although this assumption is often correct, handovers between cells depend on other parameters such as signal quality and the duration of its deterioration.

TABLE I: MSE by model and train-test ratio.

Method (Train%-Test%)	MSE
DL (90%-10%)	17.16
UMa (90%-10%)	367.24
DL (75%-25%)	24.95
UMa (75%-25%)	384.67

B. MOS Prediction

Given the predicted RSRP (according to the method explained in the previous section), we consider a similar deep learning model to predict MOS values. When the data at hand is visualized and investigated, it is clear that MOS changed with time, and according to a similar pattern for each session: there is approximately 10 seconds of buffering where the MOS is very low, then it begins to increase and starts to show the stabilized performance values. As a result, session time, which is the time from the start of the session, is added to training features in addition to vehicle coordinates and distance to the cell tower. Since the buffering does not indicate the final performance with sufficient accuracy, the first 10 seconds of each session were left out of testing. The structure of the deep neural network is the same as the previous model, except for the addition of an input node for the session time.

VI. Results and Discussion

A. Performance of DL-Based Path Loss Prediction

The predictive capability of the UMa-B with 2600 MHz along with the measurements conducted is shown in Fig.3. In this section, we use the datasets collected from the location Basaksehir. Note that UMa-B shows rather poor performance in predicting the actual RSRP values based only on the UE distance. Hence, we demonstrate how our proposed DL-based calibration can improve over UMa-B.

Let n and m are the percentage of training data and test data in the experiment, respectively. Table I compares the performance of the proposed scheme, DL, and UMA-B with different (n, m) with respect to the error metric of Mean Square Error (MSE). Note that the MSE of the proposed scheme is much lower than the traditional simple path loss model UMa-B. Also it is noticed that the train-test split of UMa means that MSE is calculated over test portion only.

Next, we consider another important performance metric, i.e., Mean Absolute Percentage Error (MAPE) and show the cumulative distribution function of MAPE in Fig. 5a. Note that approximately 90% of the predictions in test data have less than 10% MAPE, which demonstrates a very accurate prediction. Fig. 5b and Fig. 5c demonstrate how MAPE and MSE changes with respect to the distance of the user equipment from the closest cell tower. Interestingly, the error is the highest when the user equipment is approximately 100 and 250 meters away from the closest cell tower. We believe this anomaly is mainly due to the fact that the user is associated with a cell tower that may not be closest to the user at these data points.

B. Performance of DL-Based MOS Prediction

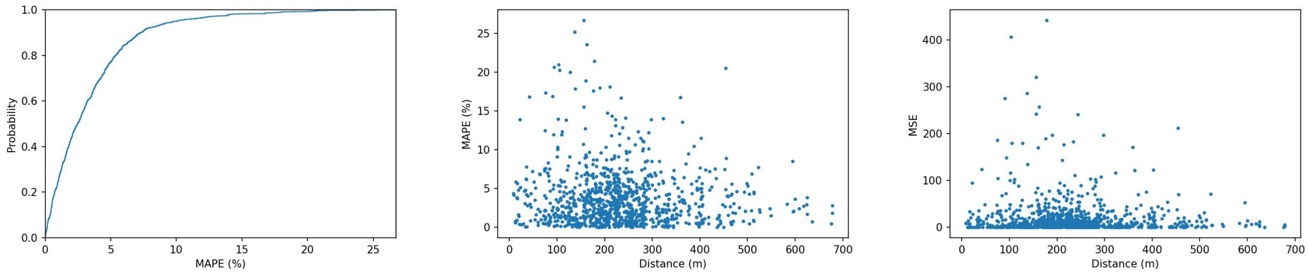
Although there exist several works in the literature that performed signal strength predictions based on machine learning models trained with real-world measurements, to the best of our knowledge, there is no other work that has addressed the prediction of QoE based on the locations of the users. We employed the method in Section V-B to establish the relationship between the distance and MAPE of predicted MOS values. For training, we employed dataset from Basaksehir (in Istanbul) with 90%-10% train-test ratio. The model outputs the predicted MOS value. Fig. 6a and 6b depict the change in MAPE with respect to distance and session time respectively. MAPE of MOS predictions are predominantly lower than 20% with respect to the vehicle's distance to the closest cell tower. Nevertheless, as was the case for RSRP predictions, MAPE is the highest when the distance is between 150 and 300 meters. We believe the reason for this anomaly is as explained before. In Fig. 6b, we depict how accurate the prediction is for varying session times. Recall that session time refers to the time into the playback of the video. MAPE is predominantly less than 10% but it is higher when the session time is between 10 and 20 seconds. We believe this interval is particularly important for playback, since most of the quality degradation occurs here due to the inadequate buffering in earlier parts.

C. Transfer Learning

Since provinces and even districts differ vastly from each other in terms of geographical conditions and cell tower placement; using only one model for every area would not be beneficial as the accuracy of the model would decline significantly in places where the data that is used to train the model did not come from. This was confirmed when predictions for another data collection from Kadikoy with the model trained from Basaksehir yielded a MAPE of 2228%. On the other hand, training a deep neural network for each area would require a high amount of time and power. To solve this challenge, the initial model from Basaksehir was trained further with the Kadikoy dataset, with the thought that it would be quicker than training it from the very beginning. To test the speed of training and the accuracy of this transferred model, another model is trained only with the Kadikoy dataset. The transferred model automatically stopped training at the 42^{nd} epoch, whereas the model that is trained from the beginning took 178 epochs. The predictions with the transferred model result in a MAPE of 3.9%, while the other model's predictions result in a MAPE of 3.75%. These results demonstrate that transferring models between different areas has a significant advantage from the training speed and lower data needs perspectives, with a nigh-negligible decrease in performance.

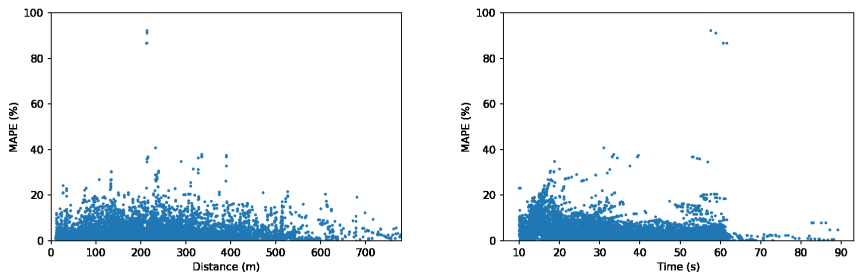
VII. Conclusion and Future Work

This paper has presented a channel model obtained using Deep Learning (DL) techniques with a simple path loss model to do the predictions of the path loss and QoE. It considers path loss modeling techniques offered by state-of-the-art stochastic models and a ray-tracing model for comparison and evaluation.



(a) Cumulative Distribution (CDF) of MAPE. (b) MAPE with respect to distance. (c) MSE with respect to distance.

Fig. 5: The prediction performance for path loss. The results are depicted for only test data.



(a) MAPE vs. vehicle distance. (b) MAPE vs. session time.

Fig. 6: MOS prediction performance with MAPE (mean absolute percentage error). The results are depicted for only test data.

The result validates the effectiveness of the deep learning model in prediction compared with the traditional simple path loss model UMa-B. As future work, an improved model for path loss prediction -to use in mobile communication systems-based on a DL framework utilizing auxiliaries such as satellite imagery can be explored for augmented QoE prediction.

References

[1] Tsolkas D., Liotou E., Passas N., and Merakos L., “A survey on parametric QoE estimation for popular services,” *Journal of network and computer applications*, vol. 77, pp.1–17, Jan. 2017.

[2] Bouraqia K., Sabir E., Sadik M., and Ladid L., “Quality of experience for streaming services: measurements, challenges and insights,” *IEEE Access*, vol. 8, pp.13341–13361, Jan. 2020.

[3] Nightingale J., Salva-Garcia P., Calero J.M.A., and Wang Q., “5G-QoE: QoE modelling for ultra-HD video streaming in 5G networks,” *IEEE Transactions on Broadcasting*, vol. 64, no. 2, pp.621–634, Apr. 2018.

[4] 3GPP, “Telecommunication management; Subscriber and equipment trace; Trace concepts and requirements,” 3rd Generation Partnership Project (3GPP), Technical Specification (TS) 32.421, 04 2021, version 17.1.1. [Online]. Available: https://portal.3gpp.org/desktopmodules/Specifications/SpecificationDetails.aspx?specificationId=2008.

[5] Aroussi S. and Mellouk A., “Survey on machine learning-based QoE-QoS correlation models,” in 2014 Int. Con. on Computing, Management and Telecommunications (ComManTel) IEEE, April 2014, pp. 200–204.

[6] Gomez-Barquero D., Li W., Fuentes M., Xiong J., Araniti G., Akamine C., and Wang J., ”Special issue on: 5G for broadband multimedia systems and broadcasting,” *IEEE Transactions on Broadcasting*, vol. 65, no. 2, pp.351–355, Jun. 2019.

[7] Msakni H.G. and Youssef H., “Is QoE estimation based on QoS parameters sufficient for video quality assessment?” *2013 Int. Wireless Communications and Mobile Computing Conference (IWCMC)*, July 2013, pp. 538–544.

[8] Kougioumtzidis G., Poulkov V., Zaharis Z.D., and Lazaridis P.I., ”A Survey on Multimedia Services QoE Assessment and Machine Learning-Based Prediction,” *IEEE Access*, Vol. 10, pp.19507–19538, Feb. 2022.

[9] ITU Telecommunication Standardization Sector, ”ITU-T Rec P 1203 Models and tools for quality assessment of streamed media,” 2017.

[10] Ostlin E., Zepernick H.J., and Suzuki H., ”Macrocell path-loss prediction using artificial neural networks,” *IEEE T. on Vehicular Technology*, vol.59, no.6, pp.2735-2747, May 2010.

[11] Wen J., Zhang Y., Yang G., He Z., and Zhang W., ”Path loss prediction based on machine learning methods for aircraft cabin environments,” *IEEE Access*, vol. 7, pp.159251-159261, Oct. 2019.

[12] Thrane J., Zibar D., and Christiansen H.L., ”Model-aided deep learning method for path loss prediction in mobile communication systems at 2.6 GHz,” *IEEE Access*, vol. 8, pp.7925–7936, Jan. 2020.

[13] Jo H.S., Park C., Lee E., Choi H.K., and Park J., ”Path loss prediction based on machine learning techniques: principal component analysis, artificial neural network, and Gaussian process,” *Sensors*, vol. 20, No. 7, p.1927, Mar. 2020.

[14] Wu L., He D., Ai B., Wang J., Qi H., Guan K., and Zhong Z., “Artificial neural network based path loss prediction for wireless communication network,” *IEEE access*, vol. 8, pp.199523-199538, Nov. 2020.

[15] Mitra K., Zaslavsky A., and Ahlund C., ”Context-aware QoE modelling, measurement, and prediction in mobile computing systems,” *IEEE T. on Mobile Computing*, vol. 14, no. 5, pp.920–936, 2013.

[16] Tao X., Duan Y., Xu M., Meng Z., and Lu J., ”Learning QoE of mobile video transmission with deep neural network: A data-driven approach,” *IEEE Journal on Selected Areas in Communications*, vol. 37, no. 6, pp.1337–1348, Mar. 2019.

[17] Alhammadi A., El-Saleh A., and Shayea I., ”MOS Prediction for Mobile Broadband Networks Using Bayesian Artificial Intelligence,” *2021 International Conference on Artificial Intelligence and Computer Science Technology (ICAICST)*, June 2021, pp. 47–50.

[18] Gokcesu H., Ercetin O., Kalem G., and Ergut S., ”Virtual Drive-Tests: A Case for Predicting QoE in Adaptive Video Streaming”. arXiv preprint arXiv:2107.12068, 2021.

[19] Lee T.H., Chang L.H., and Chan Y.S., ”An Intelligent Handover Mechanism Based on MOS Predictions for Real-Time Video Conference Services in Mobile Networks,” *Applied Sciences*, vol. 12, no. 8, p.4049, Jan. 2022.

[20] ”Study on channel model for frequencies from 0.5 to 100 GHz, version 16.1.0,” 3GPP, Sophia Antipolis, France, 3GPP Rep. (TR) 38.901, 2020. [Online]. Available: http://www.3gpp.org/DynaReport/38901.htm.