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Machine Learning Based Radio Environment Map Construction for Cellular Networks

Vasileios P. Rekkas(1), Sotirios P. Sotiroudis(1), Zaharias D. Zaharis(2), George Koudouridis(1), Panagiotis Sarigiannids(3), George K. Karagiannidis(2), Christos G. Christodoulou(4), and Sotirios K. Goudos(1)

(1) ELEDIA@AUTH, School of Physics, Aristotle University of Thessaloniki, Thessaloniki, Greece,
e-mail: {vrekkas, ssoti, georkou, sgoudo}@physics.auth.gr
(2) School of Electrical and Computer Engineering, Aristotle University of Thessaloniki, Thessaloniki, Greece
Email: {zaharis, geokarag}@auth.gr
(3) Department of Informatics and Telecommunications Engineering, University of Western Macedonia, Kozani, Greece
Email: psarigiannidis@uowm.gr
(4) Department of Engineering and Computing, The University of New Mexico, USA
e-mail: christos@unm.edu

***Abstract*—Radio environment maps (REMs) can characterize a parameter of interest in a communication channel such as the reference signal received power (RSRP) at every point in a given geographical region. High-precision REMs have substantial potential for managing wireless resources and monitoring the spectrum. In this work, we explore various machine learning (ML) models, including an ensemble approach, to construct REMs by first estimating RSRP values in a long-term evolution (LTE) network. The simulation results indicate that the proposed ensemble approach exhibits great accuracy in RSRP estimation in LTE networks.**

I. Introduction

Effective radio coverage planning is crucial in wireless cellular networks. Consequently, there is a crucial need to precisely ascertain the reference signal received power (RSRP) of signal receivers, a task that is addressed by wireless propagation models. However, the ongoing urbanization trend has introduced a myriad of complex buildings, significantly complicating the communication landscape. The intricate interplay of radio wave propagation within various complex urban structures poses a formidable challenge in developing an effective wireless propagation model capable of accurately estimating RSRP in an urban environment [1].

REMs function as tools that provide specific channel metrics, such as received signal strength, power spectral density, or channel gain, within a defined geographical area. Their utility extends to diverse applications, including network planning, interference coordination, power control, spectrum management, resource allocation, handoff procedure design, dynamic spectrum access, and cognitive radio. Radio map modeling stands as a critical technique within wireless communication, providing top-notch services tailored for future scenarios envisioned in the context of 6G networks [2].

In this study, we utilize four machine learning (ML) models, namely gradient-boosting decision tree (GBDT), light gradient boosting machine (LGBM), extreme gradient boosting (XGB), and extremely randomized trees (ET), and a mean ensemble model using the previous methods as base learners, to estimate the RSRP values in a long-term evolution (LTE) network.

II. Measurement Campaign

The training and validation process for the various ML techniques in this study was carried out using genuine data derived from an extensive and meticulous measurement campaign carried out in Oslo, Norway during the summer of 2019 [3]. Passive measurements were made across four LTE bands, including guard bands (Bands 1, 3, 7, and 20), with three LTE operators identified. To ensure reliability and thoroughness, measurements were carried out in various city areas and scenarios. In this work, the outdoor driving scenario is utilized, which involves outdoor measurements through public transport. RSRP measurements were conducted for the different frequency bands marked with various attributes:

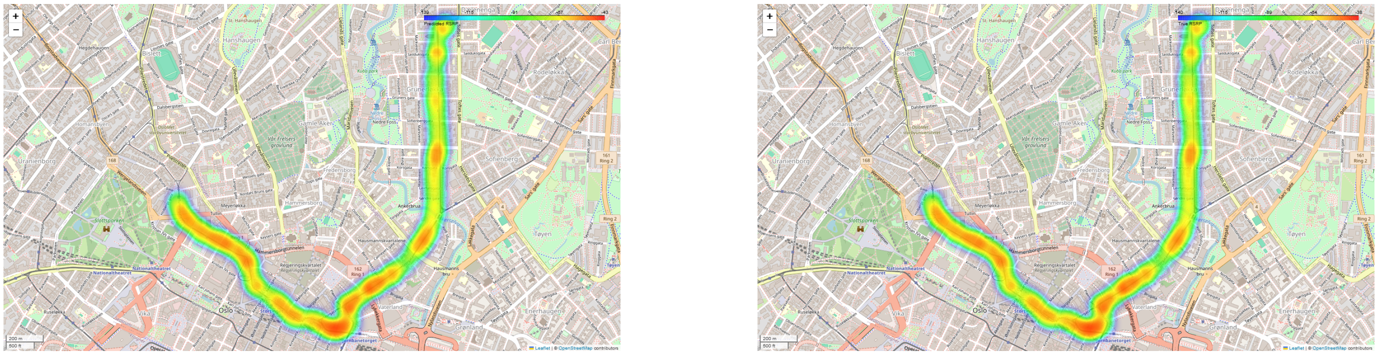
- Longitude, latitude, altitude.
- Moving speed of the device.
- Direction the device is facing.
- Frequency.
- Drift information.

For further information regarding the measurement campaign, please refer to [3].

III. Simulation results

Over the past few years, there has been growing interest in utilizing ML techniques for channel modeling. This is driven by the need to address the challenges posed by the site-specific and complex requirements of deterministic methods, as well as the limitations arising from inaccuracies in stochastic approaches. One specific approach within ML is the ensemble method, where multiple models, often referred to as "weak learners" due to their diversity, are trained, and their results are integrated to enhance the overall predictive capability.

In this research, four distinct ML models—specifically GBDT, LGBM, XGB, and ET —are employed. Additionally, a mean ensemble model is utilized, incorporating the aforementioned methods as base learners. The primary objective is to predict RSRP values within the LTE network. The evaluation of the predictive performance of the ML models is quantified through commonly used numerical metrics, including the mean absolute error (MAE), root mean squared error (RMSE), and



(a) Radio map of true RSRP values

(b) Radio map of predicted RSRP values

Fig. 1. Radio Environment Maps

mean absolute percentage error (MAPE). Additionally, the training and inference time of the models are also considered evaluation metrics, under the same hardware conditions. The models are evaluated based on the aforementioned metrics, depicted in Table I. The models are evaluated based on the aforementioned metrics, depicted in Table I, to ensure a comprehensive and effective assessment.

TABLE I
ERROR MEASUREMENT METRICS FOR RSRP PREDICTION

Algorithm	**MAE (dBm)**	**RMSE (dBm)**	**MAPE (%)**	**Execution Time (s)**	**Inference Time (s)**
GDBT	3.27	4.437	3.34	9.15	0.04217
LGBM	2.97	4.13	3.05	0.67	0.00604
XGB	3.14	4.56	3.21	7.23	0.02564
ET	3.96	5.98	3.93	2.82	0.08732
Ensemble	2.73	3.87	2.86	20.1	0.17455

The ensemble approach outperforms individual algorithms, surpassing all other methods across all previously mentioned performance indicators. Based on the estimated RSRP values of the ensemble model, a radio environment map is designed in Fig. 1 to produce a low-dimensional map of high-dimensional data. Fig. 2 displays a scatter plot showcasing the correlation between the true values and the predicted RSRP.

IV. CONCLUSIONS

In this study, four distinct ML methods are utilized to predict RSRP values in an LTE network over four guard bands. A proposed ensemble model, employing a mean prediction technique with these learners, was also explored. The results demonstrate that all approaches can efficiently predict signal power values, with the ensemble technique outperforming other individual learners, achieving MAPE below 3%. This suggests that ensemble machine learning approaches provide a viable solution for RSRP prediction. Future endeavors involve extending and testing this framework for 5G/B5G wireless narrowband Internet of Things (NB-IoT) networks and assessing the framework in more complex scenarios.

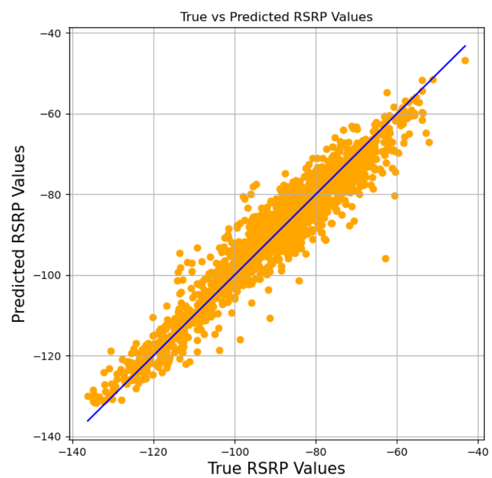


Fig. 2. Predicted versus true RSRP values

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