URSI GASS 2021, Rome, Italy, 28 August - 4 September 2021

Machine Learning for the Estimation of WiFi Field Exposure in Complex Indoor Multi-Source Scenario

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Abstract

This paper presents the preliminary results on the use of Machine Learning (ML) for the estimation of the electric-field exposure in indoor scenarios with multiple WiFi sources. Differently from similar previous approaches, the present approach aims to design a Neural Network (NN) capable to address complex indoor scenarios that include not only down-link transmission by access points (APs) but also up-link transmission by several clients (e.g., laptop, printers, tablets, and smartphones). The NN was trained and tested on the field generated by multiple WiFi sources (2400 MHz) in an office indoor setup; the 'target' exposure field in such a scenario was derived using a deterministic indoor network planner method. The median prediction accuracy of the 'target' field exposure by the proposed NN was 0.0 dB (1st quartile: -0.7 dB; 3rd quartile 0.9 dB), with a root mean square error of 2.1 dB. The proposed approach is fast (the NN training lasts about 30 minutes) and could be useful to assess radio-frequency (RF) exposure in complex indoor scenarios.

1 Introduction

Assessment of indoor RF exposure is not trivial due to the complexity and variability of the setup, which might include sources of different types (i.e., APs vs. clients) that are placed at variable positions. Such a complex and variable scenario cannot be addressed by using deterministic approaches only (such as in [1-4]): it requires also the application of novel advanced statistical approaches such as stochastic dosimetry or ML. Recently, stochastic dosimetry was applied to assess how the variability of the position of a WiFi source affects the dose of exposure in an indoor setup [5,6]. ML was found to be a computationally efficient approach to estimate indoor field exposure [7-9]. As such, ML is gaining an ever-increasing interest for solving complex and real-life applications characterized by a high degree of variability.

To the best of the authors' knowledge, all past studies based on a ML approach estimated the field exposure in quite simple scenarios that addressed only wave propagation under down-link (DL) transmission by one or multiple APs.

Our approach is innovative as we aim to develop a new and more generalized NN model capable to estimate the field exposure in more complex and realistic setups which include not only DL transmission by APs and but also up-link (UL) transmission by different sources (e.g., laptop, printers, tablets, smartphones). The proposed method is here evaluated for indoor WiFi exposure at 2400 MHz, which is a significant contribution to the overall RF exposure in our daily lives [4].

2 Methods

In the proposed method, a feed forward NN is designed to estimate the field exposure in a multi-source indoor setup that included both WiFi APs and WiFi clients. As seen in Figure 1, the setup used to train and test the NN resembled a realistic indoor layout.

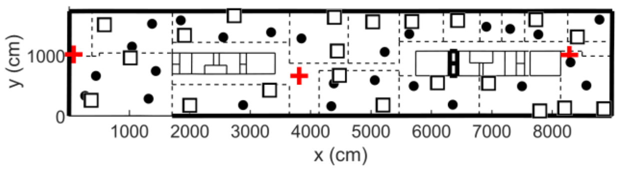

Figure 1. Layout of the analyzed indoor scenario. Thin solid lines are walls made by concrete (10 dB penetration loss), dashed lines are layered drywall (2 dB penetration loss) and thick lines are metal walls. Cross symbols are WiFi APs, white squares are WiFi clients such as printers, laptops and TVs, and circles are other WiFi users, such as smartphone/tablet users.

The setup consisted in an office building (90 x 17 m^2) with walls of different materials. Inside the building we placed three WiFi APs (height: 250 cm above the ground; maximal Equivalent Isotropically Radiated Power: 20 dBm; operating band: 2.437 GHz), 21 WiFi-only clients, e.g., printers, TV, laptops, and 25 WiFi users, such as smartphones and tablets (height: 130 cm above ground). WiFi UL power was set at 20 dBm as well, with a duty cycle of 2% [10].

The electric field E (V/m) generated in such a layout was calculated by using the WHIPP heuristic planning algorithm [3, 11-13]. Such electric field was here considered as the 'target' field exposure that our NN has to predict. The 'target' electric field was derived on a 20-cm regular grid spanning the entire building, thus giving a dataset of 38794 samples of E.

The sample dataset was divided into three disjoint subsets containing 72%, 8%, and 20% of the samples, respectively, where the first subset was used to train the NN, the second to validate, and the last one to test the NN.

The NN was trained using the Levenberg-Marquardt backpropagation method [14,15], which aims to iteratively minimize the Training Mean Square Error *TMSE* between the field exposure predicted by the NN and the target field exposure:

$$TMSE = \frac{1}{N_T}\sum_{k=1}^{N_T}\left[E_{pred_k} - E_{true_k}\right]^2 \qquad (1)$$

where N_T is the number of samples in the training set, E_{true_k} is the target field exposure at position k and E_{pred_k} is the field exposure predicted by the NN at position k. To prevent NN overfitting to the training data, we calculated also the Validation Mean Square Error *VMSE* on the validation set (using (1) on the N_V samples of the validation set) and stop the training when *VMSE* increased, meaning that the NN started to perform poorly because of overfitting to the training samples. Finally, we determined the optimal numbers of hidden layers of the NN by using the cross-validation method [16] using K=10 partitions.

For each position of the 38794 available in the sampled grid, we determined the number of APs, the number of WiFi clients/users, the number and the average penetration loss of non-metallic walls, and the number of metallic walls at distances from 50 cm to 5 m with a step of 50 cm. As a result, each of the 38794 positions in the sampling grid was characterized by a 60-element vector that was used as the input to the NN to predict the exposure at that position.

The prediction accuracy of the NN was measured by calculating the bias Δdb and root mean square error $RMS_{\Delta db}$ between the predicted and the target electric field:

$$\Delta db_k = 20\log_{10}\frac{E_{pred_k}}{E_{true_k}} \qquad (2)$$

$$RMS_{\Delta db} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\Delta db_k{}^2} \qquad (3)$$

where N is the number of samples.

3 Results

Figure 2 shows the distribution of the 'target' electric field in the analyzed indoor setup.

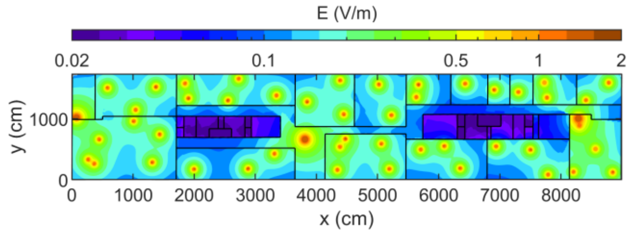

Figure 2. Electric field E (V/m) inside the analyzed building.

The median value of the target electric field inside the analyzed indoor setup was 190 mV/m (1st quartile Q1: 140 mV/m; 3rd quartile Q3: 260 mV/m; SD: 183 mV/m).

The best NN was achieved by using 5 hidden layers. With such an optimized NN, the MSE calculated on the training set (*TMSE*) was 32×10^{-4} $(\text{mV/m})^2$, the MSE on the validation set (*VMSE*) was 29×10^{-4} $(\text{mV/m})^2$ and the MSE on the test set was 39×10^{-4} $(\text{mV/m})^2$. The MSE on the test set was slightly higher than that of the training and validation set, meaning that, as expected, the prediction accuracy of the NN was slightly worse for the test set. However, because the MSE of the test set was very similar to that of the training and validation set, we could comment that the NN had a good accuracy even in the worst case, that is when it was fed with the test set, i.e., with data never used either during training or validation.

Figure 3 shows the difference between the electric field predicted by the NN and the 'target' electric field, as calculated using the samples of the test set.

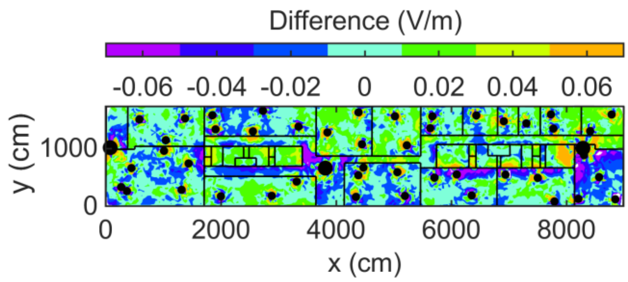

Figure 3. Difference between the electric field (V/m) predicted by the NN and the target electric field calculated on the samples of the test set. The black dots show the position of WiFi sources.

For the worst case condition in Figure 3, i.e., when using the samples of the test dataset, the NN achieved a very good median bias *Δdb* between the predicted and the 'target' electric field equal to 0.0 dB (Q1: -0.7 dB; Q3: 0.9 dB) and a root mean square error $RMS_{\Delta db}$ of 2.1 dB.

4 Discussion and Conclusion

We investigated the feasibility and accuracy of using a NN approach to predict the field exposure generated by multiple WiFi sources in an indoor scenario. The proposed NN approach could address more complex exposure scenarios than those typically addressed in past ML studies, as it could model the contribution of both DL and UL transmissions to the overall field exposure.

The NN was trained using the field distribution of an indoor scenario - an office building - whose characteristics resembled those typically found in realistic indoor setups, which included walls at different position/orientations made by different materials, multiple APs, and several WiFi clients at different positions inside the scenario.

To predict the field exposure, the NN was fed with input data that could be derived very easily, such as the number and type (AP vs. clients) of WiFi sources, the number of non-metallic and metallic walls, and the average penetration loss of non-metallic walls at distances increasing from 50 cm to 5 m from the point in the room where the electric field had to be estimated. As such, once trained, the NN could be used for calculating the field exposure only using the simple input data described above.

The proposed NN predicted the field exposure with a median error over the entire 90x17 m^2 area of the building equal to 0.0 dB and a RMS of 2.1 dB.

Previous ML approaches addressed exposure setups less complex than in our study. For example, [8] considered an indoor setup with several APs (but with no clients). The average absolute error between the target and the ML-predicted field excitation ranged from 2.9 dB to 4.0 dB. In [7], a NN is used to predict the electric field generated indoor by a single antenna operating in the 900 MHz band; the mean prediction error of such a NN ranged from -5.3 dB to 2.4 dB. In [9], NNs are applied to model the field exposure generated at 900, 1800, 2100, and 2400 MHz by several APs; this latter NN achieved a mean error of 0.7 dB and SD of 5.22 dB.

Our NN achieved a performance comparable or even better than in the above reviewed studies that addressed scenarios less complex than in our study. As a matter of fact, the median value of the prediction error of the field exposure with our NN was 0 dB.

To conclude, the preliminary results obtained with the proposed approach revealed that NNs might be successfully applied to estimate the field exposure in a multi-source WiFi indoor scenario. As the next steps, we are investigating and testing the degree of generalization of the proposed NN in additional indoor scenarios, by varying the geometrical layout of the building and other variables relating to the sources, e.g., sources' height from ground, number and position of APs, etc.

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