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A Deep Learning-Based Strategy to Predict Self-Interference in SFN DTT †

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Abstract: A deep learning-based strategy for the analysis of the self-interference in single frequency networks (SFNs) for digital terrestrial television (DTT) broadcasting is considered. Several laboratory measurements were performed to create a dataset that relates the self-interference parameters and some quality metrics of the resulting received signal. The laboratory setup emulates an SFN scenario with two DTT transmitters. The strongest received signal and the relative values of attenuation and delay between the signals stand for the input parameters. The modulation error ratio (MER) of the strongest received signal, the MER of the resulting signal, and the SFN gain (SFNG) are the output parameters. This dataset is used to train four different multi-layer perceptron (MLP) models to predict accurate maps of interference and signal quality metrics. The considered models are suitable as complements for any multiple frequency network (MFN) coverage software with the capability to return the signal strength and the position data. This way, the SFN self-interference behavior can be predicted by considering only a proper description of the MFN coverage.

Keywords: SFN; deep learning; broadcasting; self-interference

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1. Introduction

The remarkable growth of mobile services and wireless communication technologies has led to a revision of the way the available spectrum bands are allocated. In digital terrestrial television (DTT) broadcasting, the spectral efficiency achieved with multiple frequency networks (MFNs) is significantly improved when moving to single frequency networks (SFNs). Furthermore, the deployment of SFNs leads to a more homogeneous distribution of the electric-field strength in the coverage area and to savings in transmission power [1].

In previous works, self-interference in SFNs is only considered when the interfering signals arrive with a delay longer than the guard interval. However, this only represents a critical scenario where the interference is mostly destructive. Signals arriving within the guard interval also produce self-interference, and it can be either constructive or destructive. The effect of this kind of interference is called SFN gain (SFNG) and it must be properly controlled to obtain a good performance in SFN systems [2–4].

Several network planning strategies based on deep learning (DL) algorithms are being considered as a reasonable alternative for the configuration of broadcasting systems. These strategies allow reducing the computational complexity of theoretical models and the planning cost of the field-testing-based approaches [5–7]. The predictive capability of DL algorithms and the lack of works about using them for SFN interference analyses have motivated this research. The major contributions of this work can be summarized as follows:

- The development of a laboratory test-based dataset that relates the parameters of the received signals to several metrics of interference and signal quality.
- The implementation of deep learning-based models to predict the interference and the resulting signal quality metrics.

2. Dataset and Proposed Deep Learning-Based Models

The proposed laboratory setup emulates an SFN scenario with two interfering transmitters. The interfering signals were generated by using a Broadcast Test Center (BTC) from Rohde and Schwarz and the signal quality metrics were measured by using the S7000 TV Analyzer professional receiver. The electric-field strength of the main signal ($E_{\mathrm{MainSignal}}$), and the values of *Attenuation* and *Delay* of the secondary signal, were configured to emulate self-interference scenarios. These parameters are the input features in the proposed dataset. The modulation error ratio (MER) was the metric employed to quantify the signal quality. The measured values of modulation error ratio (MER) of both the main signal (MER_{MFN}) and the resulting received signal (MER_{SFN}) are output features. The SFN gain (G_{SFN}) is the third output feature, which is calculated as the difference between the MER_{SFN} and the MER_{MFN} parameters.

The resulting dataset was employed to train four multi-layer perceptron (MLP) models by using a supervised-learning strategy (Table 1). The first models are regression models; thus, they were trained to predict the exact values of their respective output features. The last one is a binary classification model and it was trained to predict whether the value of G_{SFN} is positive or negative. Positive G_{SFN} values stand for the cases where the received signal improves when moving to SFN while the negative values correspond to a signal degradation.

Table 1. Proposed deep learning-based models.

MLP Models	Output Feature	Type
MLP_MfnMER	MER_{MFN}	Regression
MLP_SfnMER	MER_{SFN}	Regression
MLP_SfnG	G_{SFN}	Regression
MLP_SfnGclass	$Gclass_{\mathrm{SFN}}$	Classification

3. Results

Table 2 summarizes the accuracy values obtained by employing the proposed regression models. The coefficient of determination (R^2), the mean absolute error (MAE), the mean square error (MSE) and the root mean square error ($RMSE$) are the metrics used to measure the performance. A lower accuracy is obtained with the MLP_SfnG model since the correspondence between G_{SFN} and the input features cannot be easily determined.

Table 2. Performance metrics of the regression models.

MLP Models	R^2	MAE	MSE	$RMSE$
MLP_MfnMER	0.998	0.159	0.036	0.191
MLP_SfnMER	0.997	0.134	0.041	0.203
MLP_SfnG	0.909	0.151	0.049	0.221

In Figure 1, the predicted values are plotted versus the measured values. As expected, a higher dispersion can be observed in the G_{SFN} predictions because the performance of this model is lower than the others. Some dispersion can also be observed in the edge values of the parameters due to the instrument measuring ranges.

Figure 2 shows the confusion matrix for the MLP_SfnGclass classification model. From the 317 samples considered for the validation process, the 91.5% were well predicted

(184 true negatives and 106 true positives). The remaining 8.5% of the predictions were either false positives or false negatives.

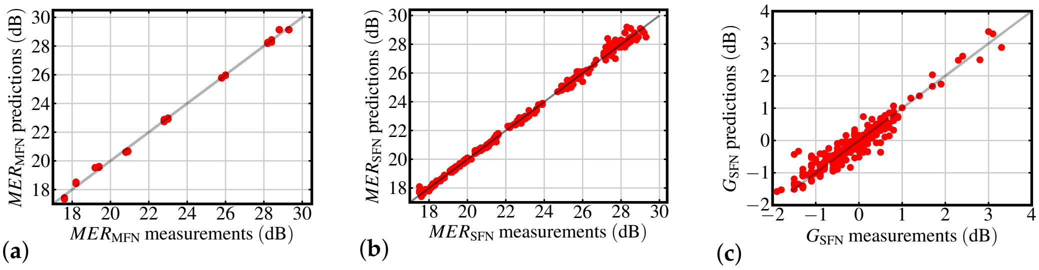

Figure 1. Predicted values versus measured values of (**a**) MER_{MFN}, (**b**) MER_{SFN} and (**c**) G_{SFN}.

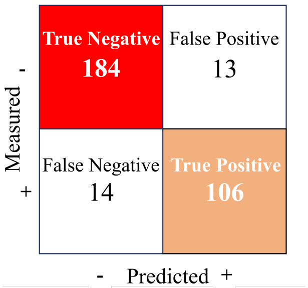

Figure 2. Confusion matrix of the MLP_SfnGclass model.

4. Conclusions

This paper proposes a deep learning-based strategy to analyze the self-interference in SFNs for DTT broadcasting. Unlike most planning-oriented researches, interference in SFNs is analyzed over the entire overlapping area and not only in critical cases where delays are especially long. A dataset obtained from laboratory measurements is employed to train four MLP models for predicting signal quality parameters in an SFN DTT deployment. The prediction results exhibit the high degree of relation between the received signal's parameters and the resulting signal quality. The proposed dataset and the MLP models are suitable for any SFN interference analysis since this approach is not limited to specific terrain or transmission variables.

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Data Availability Statement: The dataset used to train the deep learning-based models is publicly available at https://github.com/DarielPereira/SFN_Dataset.git (accessed on 30 September 2021).

Conflicts of Interest: The authors declare no conflict of interest.

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