From MFN to SFN: Performance Prediction through Machine Learning

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Abstract— **In the last decade, the transition of digital terrestrial television (DTT) systems from multi-frequency networks (MFNs) to single-frequency networks (SFNs) has become a reality. SFN offers multiple advantages with respect to MFN, such as a more efficient management of the radioelectric spectrum, homogenizing the network parameters, and a potential SFN gain. However, the transition process can be cumbersome for operators due to the multiple measurement campaigns and required finetuning of the final SFN system to ensure the desired quality of service. To avoid time-consuming field measurements and reduce the costs associated with the SFN implementation, this paper aims to predict the performance of an SFN system from the legacy MFN and position data through machine learning (ML) algorithms. It is proposed a ML concatenated structure based on classification and regression to predict SFN electric-field strength, modulation error ratio, and gain. The model's training and test process are performed with a dataset from an SFN/MFN trial in Ghent, Belgium. Multiple algorithms have been tuned and compared to extract the data patterns and select the most accurate algorithms. The best performance to predict the SFN electric-field strength is obtained with a coefficient of determination (R^2) of 0.93, modulation error ratio of 0.98, and SFN gain of 0.89 starting from MFN parameters and position data. The proposed method allows classifying the data points according to positive or negative SFN gain with an accuracy of 0.97.**

Keywords— *Machine learning, MFN, SFN gain, SFN planning.*

I. INTRODUCTION

The last years have been marked by the significant proliferation of novel multimedia services, applications, and smart mobile broadband devices [1]. This evolution comes together with an unstoppable growth in data traffic, especially multimedia. The most recent forecast from CISCO [2] shows that by 2022 the video traffic will be 79 % of the total cellular data traffic.

In this context, broadcast/multicast technologies like single-frequency networks (SFNs) [3] are crucial for the existing and emerging mobile broadband standards, such as Long Term Evolution (LTE), 5G New Radio (NR), and beyond.

SFN has been assumed worldwide by telecommunication operators to save radio frequency resources and homogenize the network. However, the transition from a multi-frequency network (MFN) to an SFN might lead to multiple measurement campaigns and resource-consuming tuning processes to achieve the expected performance and quality of service (QoS). The above explanation justifies why, in the last years, several investigations have been oriented to exploit better and quantify the SFN capabilities beyond digital terrestrial television (DTT) and digital audio broadcasting [4-8].

Recently, multiple works have been conducted on the necessary broadband-broadcast convergence to enable a higher spectral efficiency for future mobile networks. Several broadcast-native concepts, such as SFN, are worthy to enable multicast-unicast service in 5G, or ATSC 3.0-5G convergence, boosting research interest in SFN planning [9-11].

The appropriate prediction of SFN metrics such as coverage, modulation error ratio (MER), potential interference, and the resulting network gain over the legacy MFN is fundamental for operators during dimensioning and planning [12]. It allows offering a satisfactory QoS to end-users and exploits the advantages of the SFN topology.

Traditionally, broadcast operators use theoretical and/or empirical propagation models to estimate network parameters and performance during the network planning phase [13]. Nevertheless, in [12], the authors exposed that the propagation models' imperfections become even more critical for the current and future generations of DTT and broadband systems.

In [14], the authors explained that the next-generation wireless networks evolve into more complex systems with multiple service requirements, heterogeneity in applications, devices, and networks. Additionally, the operators have access to large amounts of data. Therefore, they envisioned data-driven next-generation wireless networks, where the network operators employ advanced data analytics, machine learning (ML), and artificial intelligence (AI).

ML algorithms are inexpensive and powerful tools, widely used to learn data patterns by exploiting the relevant information from a previously collected dataset [15]. Recently, ML has been applied for planning and optimizing telecommunication networks and services [12, 13, 15, 16], proving its advantages over theoretical and/or empirical propagation models. ML allows predicting multiple key performance indicators of broadband and broadcast systems with high accuracy, avoiding the constant necessity of field measurements.

The previously defined situation motivates the goal of predicting the performance of an SFN system from the legacy

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MFN and position parameters through supervised ML algorithms. The proposal is based on regression ML algorithms to predict SFN electric-field strength (E), MER, and gain values. Moreover, it is proposed the use of a classification ML algorithm to predict whether the SFN gain is positive or negative.

The model's training and test process is performed with a dataset of 389 samples from an SFN/MFN trial in Ghent, Belgium. The regression algorithms are evaluated through numerical simulations using the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error ($RMSE$). Moreover, the classification algorithms are tested in terms of prediction accuracy. We prove different regression and classification ML algorithms and different ML concatenated structures to maximize the proposal performance.

The results show the potentials of ML algorithms to predict the performance of an SFN only using MFN and position data. It could reduce the risks and costs associated with the SFN implementation avoiding time-consuming, expensive measurements and the inaccuracy of theoretical and empirical propagation models. To the authors' knowledge, it is the first time that a concatenate structured of trained ML algorithms is used to predict SFN performance in terms of electric-field strength, modulation error ratio, and gain based on MFN and position data.

The remainder of this paper is structured as follows. Section II discusses related works in SFN systems and the use of ML for network planning. Section III presents the problem and system formulation. In section IV, the validation, numerical results, and analysis of the proposal are presented. Finally, in section V, the document is concluded.

II. RELATED WORKS

This section surveys the state of the art related to SFN planning and ML applications on network planning.

A. SFN Planning

This subsection covers some of the most recent works related to SFN planning and its advantages for actual broadcast and broadband technologies and beyond.

The worldwide DTT deployments have traditionally utilized MFN, a network structure that uses different frequencies in the service area [17] (i.e., with N transmitters, N frequency channels are used). However, the increasing demand of spectrum for mobile broadband services reduces the available spectrum for DTT systems.

In [3], the SFN topology was presented. This technology optimizes the spectrum resources because it provides the required coverage through multiple transmitters operating at the same frequency and carrying the same content [18]. Within the SFN coverage area, many receiving locations could be served by more than one transmitter. It introduces a certain redundancy level during signal reception improving service availability. Moreover, a more homogeneous field strength distribution is settled throughout its coverage area, enabling a potential network gain [18].

In [19], the authors proposed a methodology for calculating SFN gain in digital broadcast systems. In this paper, the SFN gain is defined as a parameter describing potential gain or interference, and it is closely related to the geographical distribution of the network. SFN gain is defined as

$$G_{SFN} = MER_{SFN} - MER_{MFN} \qquad (1)$$

where MER_{SFN} and MER_{MFN} are the modulation error ratio at a specific location within the service area. A positive or negative value of G_{SFN} means a signal improvement or degradation at each specific geographical point.

In [20], Caiwei et al. presented a methodology based on theoretical network models for planning large SFNs for Digital Video Broadcasting-T2 (DVB-T2). The authors highlighted that finding the suitable configuration is complex due to the large number of parameters involved in the process.

In [21], the authors evaluated intra-system interference in DVB-T2 SFN systems. The authors proposed a method to reduce interference by optimizing the relative delay for each SFN transmitter. They used the Longley-Rice model for predicting the propagation of radio waves and coverage areas.

In [22], the authors proposed an approach to optimize SFN planning for digital television/terrestrial multimedia broadcasting (DTMB) based on genetic algorithms (GAs). The proposal aimed to deal with the complexity of the design and deployment of SFNs.

The advantages of the broadcast network structure and planning concepts have been presented in recent broadband technologies for broadcast and multicast applications. For LTE and LTE-Advanced services, SFN plays a key role. It was introduced in Release 9 of the 3rd Generation Partnership Project (3GPP) as a multimedia broadcast single frequency network (MBSFN), where the same content is transmitted to a group of users in a cell using a subset of available resources [23]. Likewise, SFN is determinant for the broadcast/multicast services over 5G networks, reducing interference and handover rates between physical cells and contributing to the users' QoS [8].

In [5], the authors proposed a dynamic MBSFN area formation algorithm for multicast service delivery in 5G NR networks to enable the simultaneous transmission of the same content within multiple cells over the same radio resources, improving network scalability and spectral efficiency.

In [24], He-Hsuan et al. presented a flexible partitioning method for SFN areas in the emerging NR multimedia broadcast multicast service (MBMS), enabling a more flexible network structure, and resources usage. The authors identified that the system performance could be improved by developing an adequate SFN area and interference handling planning.

In [25], the authors proposed a model selection algorithm for multicast service delivery between MBSFN and single-cell point to multipoint (SC-PTM). The proposal exploited the trade-off between the utilization of user diversity via SC-PTM and the extra SFN gain from MBSFN.

The works presented above help to understand the essential capabilities of SFN technology for actual and future television and broadband standards. Nevertheless, throughout these papers, we can agree on the complexity of SFN planning in terms of multiple network variables, QoS parameters, interference handling, and the requirement for extensive measurement campaigns. Moreover, none of these papers take advantage of the ML algorithms that recently have been used as a powerful tool for wireless network planning. In contrast,

our proposal applies an ML concatenated structure to predict the performance of an SFN from legacy parameters of the MFN and position data.

B. ML Prediction for Network Planning

This subsection covers some of the most recent works related to ML prediction for network planning. The research shows the potential of using regression and classification ML algorithms to estimate broadcast/broadband network parameters during the planning phase.

As described in [26], ML is a research field at the intersection of statistics, AI, and computer science, also known as predictive analytics or statistical learning. In [27], ML is defined as "the science (and art) of programming computers so they can learn from data."

In [12], the authors proposed a novel DTT coverage prediction method using several ML regression algorithms and field strength measurements. The best performance was achieved with random forest (RF) [28] compared to Adaboost regression [29], K-nearest neighbors (KNN) regression [30], and ordinary kriging [31] algorithms.

In [32], ML algorithms were used to learn path gain based on terrain elevation features. The results showed an 8 dB improvement compared with a traditional empirical model.

Reference [33] presented a network planning tool based on GA and supervised ML algorithms [34]. The presented analysis demonstrated that the proper exploitation of data and experience through data analysis could add value to the operators during the planning and deployment of networks.

In [35], the authors suggested using neural network (NN) algorithms [36] to predict signal to interference ratio. They recommended the radial basis network algorithm as a method for coverage map prediction.

In [15], a received signal strength prediction strategy based on ML was proposed for coverage evaluation in 5G networks. The authors evaluated the performance employing different ML algorithms. The results showed that support vector machine (SVM) [37] outperformed other classification algorithms regarding prediction accuracy, up to 0.87.

In [38], the authors proposed cellular network power control optimization by using the unsupervised K-means algorithm [39]. They evaluated the proposal in a real mobile network with positive results regarding voice quality and dropped call rate.

In [16], the authors proposed an artificial NN based on multilayer perceptron (MLP) [40] for path loss prediction in a wireless communication network. The authors' proposal aimed to understand the propagation characteristics of radio waves and provided a theoretical basis for wireless network optimization and communication system design.

The investigations mentioned above represent a good benchmark to address wireless network planning from an ML approach. These papers prove the advantages of ML algorithms predicting coverage, handling interference, and helping to reduce the complexity and uncertainty associated with network planning. In this framework, our proposal is based on supervised regression and classification ML algorithms to predict SFN E, MER, and gain by employing a dataset resulting from an SFN/MFN trial in Ghent, Belgium.

III. PROBLEM AND SYSTEM FORMULATION

Our proposal aims to help to reduce the complexity and performance uncertainty during the transition from an MFN to an SFN and the corresponding network planning. This research intends to show the possibility of having a performance estimation of an SFN from collected data about the legacy deployed MFN, position information, and ML algorithms.

The proposal formulation comprises three major phases, shown in Fig. 1: data collection and preparation, ML algorithms training according to the target SFN parameters to predict, and proposal of concatenated structures of the trained ML algorithms to improve the prediction's performance. In the following subsections, we detail these phases.

A. Phase 1: Data Collection and Preparation

In [19], Plets *et al.* presented the results of a measurement campaign realized in Ghent, Belgium (Fig. 2). The measurements were taken along a 50 km route around three base stations (Tx1, Tx2, Tx3) in a mixture of a suburban and an urban environment.

The authors used four network configurations to alternate between MFN and SFN. In one of the configurations, all the transmitters were active and synchronized in SFN mode. In each of the remaining scenarios, only one of the transmitters was active, being the rest switched off. Then, at each sample point along the track, they collected the position data (GPS coordinates), E [dBµV/m], and MER [dB] relative to the four network configurations. Spatial synchronization among the
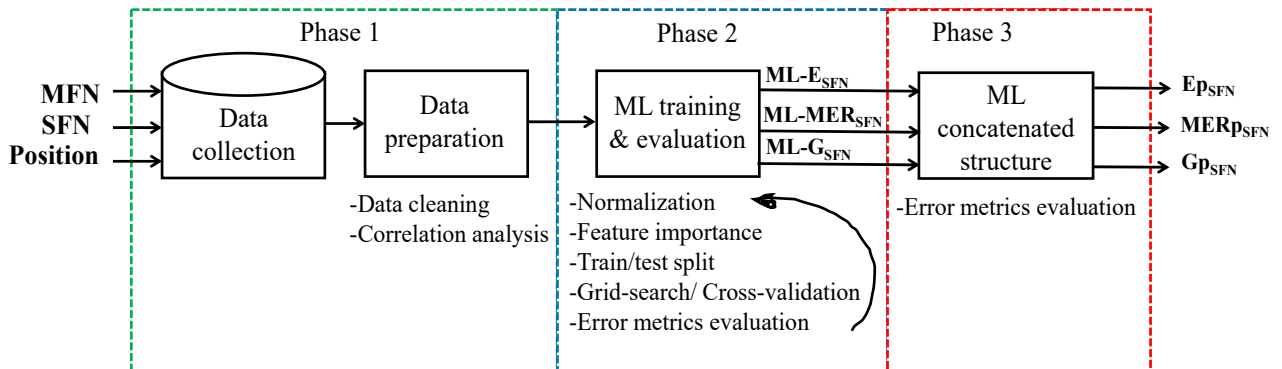

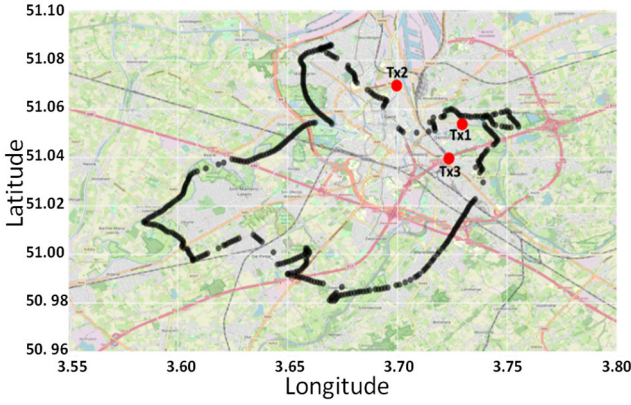Fig. 1. General workflow of the proposal.

Fig. 2. Map of Ghent with the three base stations (red circles) and the measurement route's indication.

four tracks was obtained via a map-matching procedure [41]. The resulting dataset stores 389 points with 27 registered variables related to position information, MFN, and SFN parameters. The details about this measurement campaign are described in [19].

Table I shows the registered parameters for each sample point. The collected data can be divided into three main categories: position, MFN, and SFN data. The position' variables give the specific measurement point coordinates and relative information concerning the transmitters' location. The MFN data are the measured E, MER received from each transmitter and their corresponding standard deviations. These data at each location are what we assume as legacy deployed MFN. The SFN data are E, MER, gain (resulting from applying (1) to the measured MER values), and corresponding standard deviations.

Beside the data preparation, we check for outliers across the collected variables E (E_{MFN}, E_{SFN}), MER (MER_{MFN}, MER_{SFN}), and the resulting SFN gain (G_{SFN}). We identify that the G_{SFN} variable presents several outliers, as we show in Fig. 3. At the same time, E and MER do not present outliers in the collected data.

Fig. 3 shows the density and quantitative distribution of the G_{SFN} variable. This representation facilitates the categorization of a variable in different levels. The upper box shows the quartiles of the G_{SFN} variable, while the whiskers extend to show the rest of the distribution, leaving out the points that are determined as outliers. As we can see, the distributions of G_{SFN} values are between ±12 dB with several outliers beyond that. Nevertheless, the first two quartiles (50
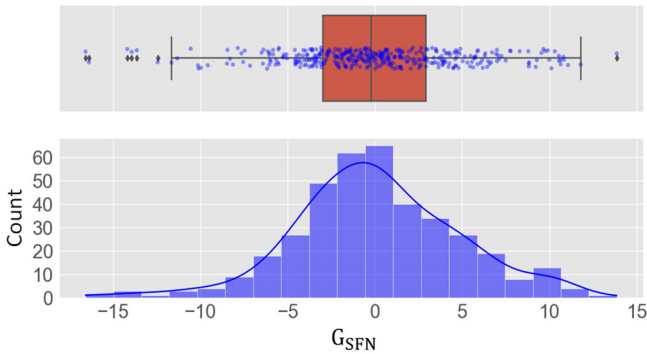

Fig. 3. Density and quantitative distribution of the SFN gain (G_{SFN}).

Type of data	Variable description	Number of variables
Position	GPS coordinates	2
	Distance to each Tx	3
	Distance difference of the closest and furthest Tx	1
	Distance difference to the two closest Tx	1
MFN	E from each Tx	3
	Highest E of the three Tx (E_{MFN})	1
	Standard deviation of MFN_E values ($Estd_{MFN}$)	1
	MER from each Tx (dB)	3
	Standard deviation of MER from each Tx	3
	Highest MER of the three Tx (MER_{MFN})	1
	Standard deviation of MFN_{MER} values ($MERstd_{MFN}$)	1
	E difference of the two strongest Tx	1
	Distance difference of the two strongest Tx	1
SFN	E value of the SFN (E_{SFN})	1
	Standard deviation of E value of the SFN ($Estd_{SFN}$)	1
	MER value of the SFN (MER_{SFN})	1
	Standard deviation of MER value of the SFN ($MERstd_{SFN}$)	1
	SFN gain (G_{SFN})	1
Total		27

Distance (m); E (dBμV/m); MER (dB); SFN gain (dB)

% of data values) are between ±3 dB.

From [19], we can conclude that SFN gain values higher than 5 dB are unrealistic for the transition from an MFN to an SFN configuration. 75 % of the dataset sample points have an absolute G_{SFN} value lower than or equal to 5 dB. Therefore, to safeguard the data reliability of our procedure, we reduce the dataset to values in this range $|G_{SFN}| \leq 5$ dB (288 samples).

Another critical step during data preparation is the correlation analysis among the variables. We focus on the main MFN and SFN performance parameters collected in the dataset: E_{MFN}, E_{SFN}, MER_{MFN}, MER_{SFN}, and G_{SFN}. Fig. 4 shows the correlation of each one of these variables with the others.

There is high correlation between the measured E value and the corresponding MER in the sample points. For a constant level of noise at the receiver end, if the E increases, the signal to noise ratio (SNR) and the resulting MER increase.

The MER is a modulation quality metric in digital communications systems [42]. It indicates the receiver's ability to correctly decode the transmitted signal, comparing the actual location of a received symbol to its ideal reference signal in the modulation constellation. From a mathematical point of view, the MER is the ratio of the E of the signal to the power of the error vector, expressed in dB [42]. Therefore, as the E of the signal degrades, the error vector of the symbols increases, and consequently, the measured MER value decreases, as shown in Fig. 4.

From Fig. 4, we can also appreciate the high correlation between E_{MFN}, MER_{MFN}, and the E_{SFN}, MER_{SFN}. This well-defined correlation means that the reception conditions and the receiver's signal quality in an MFN determine the
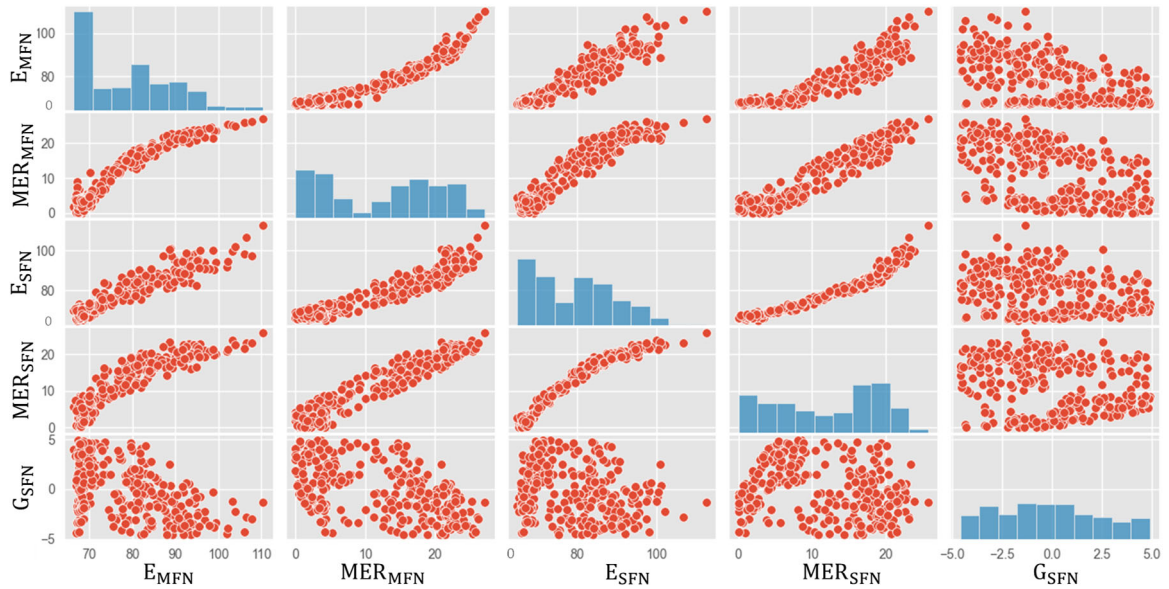
Fig. 4. Univariate distributions and pairwise relationship of E_{MFN}, MER_{MFN}, E_{SFN}, MER_{SFN} and G_{SFN}.

reception conditions and signal quality in the resulting SFN topology. Nevertheless, in the case of the G_{SFN} parameter, we can see that this variable is uncorrelated with the independent MFN and SFN parameters. It happens because the positive or negative SFN gain in a specific sample point depends only on the difference between the MER_{SFN} and MER_{MFN}, according to (1).

The SFN gain value does not directly relate to the variation of the E of the signal in MFN or SFN from one sample point to another. Moreover, as proved in [19], an improvement in the E on a specific sample point due to the transition from MFN to SFN does not imply a positive value of SFN gain. An increment in SFN E does not necessarily imply an increment in the MER signal quality. The SFN topology could introduce signal quality impairments concerning the MFN topology, even when SFN interfering signals arrive within the guard interval.

We use the well-defined correlation between the E_{MFN} and MER_{MFN} with the resulting values of E_{SFN} and MER_{SFN} as the ground base for our proposal. The ML approach takes advantage of these relations among the discussed dataset variables to train regression and classification ML algorithms to predict the performance of an SFN from the legacy MFN parameters.

B. Phase 2: ML Algorithms Training

ML algorithms could be used to solve mainly supervised or unsupervised problems. In the first case, the algorithms are trained with a dataset based on inputs (called features) and their corresponding outputs (called labels). The algorithms find and learn the patterns between the features and labels to predict further the outputs related to unseen samples of features [26, 27].

Based on the previous analysis and the preparation of the dataset, we can define our ML problem as a supervised problem according to the proposed goal. The MFN and position data are the features, and the E_{SFN}, MER_{SFN}, and G_{SFN} parameters are the specific labels.

Supervised ML algorithms can be divided into classification and regression models [43]. In the first type, the labels are discrete (e.g., to predict if a point in an SFN coverage area will have a positive or negative SFN gain). In regression models, the prediction is for continuous outcomes (e.g., to estimate the E_{SFN} value in the coverage area).

In our proposal, we aim to solve three supervised ML problems: two based on regression algorithms to predict the E_{SFN} and MER_{SFN} values (i.e., Ep_{SFN} and $MERp_{SFN}$, respectively), and the third based on classification algorithms to predict if the sample points are classified into positive or negative G_{SFN} (i.e., $Gpclass_{SFN}$). Additionally, due to the linear dependency of the gain SFN on the MER_{MFN} and MER_{SFN} values, we calculate the G_{SFN} value (Gp_{SFN}) by applying (1) with the predicted $MERp_{SFN}$ and the measured MER_{MFN} values.

In Table II, we summarize the considered regression and classification ML algorithms. The theoretical fundamentals and practical implementations of such regression and classification algorithms can be found in [26, 27, 43, 44]. The selection of the algorithms is based on the study of the related works, where the outperformance of these algorithms for wireless communications applications is proved.

As shown in Fig. 1, the ML training and evaluation phase includes the data normalization, feature importance iterative analysis, data train/test split, grid-search/cross-validation, and, finally, the evaluation of the algorithms through specific error metrics. The training and evaluation are iterative processes throughout all these steps to optimize the results according to the proposed goal.

The normalization of the input data avoiding numerical attributes with different scales is only necessary for the SVM and MLP algorithms. These algorithms are sensitive to the different scales of the MFN and position data. Therefore, this process is crucial to improve their performance. We apply the normalization method Min-Max scaling [27], transforming all features into the range [0, 1].

Feature importance is another critical process during the

TABLE II
CONSIDERED REGRESSION AND CLASSIFICATION ML ALGORITHMS

Regression algorithms (E_{SFN}, MER_{SFN})	Classification algorithms (G_{SFN})
- Gradient Boosting (GB)	- Support Vector Classification (SVC)
- Random Forest (RF)	- Gradient Boosting Classification (GBC)
- Support Vector Regression (SVR)	- Logistic Regression (LogR)
- Multilayer Perceptron Regression (MLP-R)	- Multilayer Perceptron Classification (MLP-C)

TABLE III
FEATURE RANKING OBTAINED BY MUTUAL INFORMATION FOR E_{SFN}, MER_{SFN}, AND G_{SFN}

R	SFN_E	SFN_{MER}	SFN_G
1	E_{MFN}	E_{SFN}	MER_{SFN}
2	MER_{MFN}	MER_{MFN}	MER_{MFN}
3	d to Tx 2	E_{MFN}	d diff of the two strongest Tx
4	Coordinate Y	Coordinate Y	MFN_E
5	d to Tx 3	d to Tx 2	d to Tx 3
6	MER from Tx 3	d to Tx 3	E diff of the two strongest Tx
7	E from Tx 3	d diff of the closest and furthest Tx	d diff of the closest and furthest Tx
8	E diff of the two strongest Tx	E from Tx 2	Coordinate Y
9	$Estd_{MFN}$	MER from Tx 2	d to Tx 2
10	MER from Tx 2	E diff of the two strongest Tx	$Estd_{MFN}$
11	E from Tx 2	MER from Tx 3	E_{SFN}
12	d diff of the closest and furthest Tx	Coordinate X	MERstd from Tx 2
13	d to Tx 1	E from Tx 3	E from Tx 2
14	Coordinate X	E from Tx 1	MER from Tx 3

Ranking (R); distance (d); difference (diff).

training and evaluation phase to reduce the number of essential variables based on the correlation between the features and labels. Determining the most critical features during network planning is a necessary task for any telecommunication operator. A large number of input data represents a more complex dataset and not necessarily better performance. F-test statistics [45], Mutual Information (MI) [46], and Principal Component Analysis (PCA) [47] are three methods widely utilized for dimension reduction, e.g., [13, 15, 48]. However, revealing the most relevant monitoring features is more complex with the PCA.

Considering the previous explanation, we evaluate the different ML algorithms using F-test and MI. Then, through the iterative training process, we select the method that identifies the best subsets of features to maximize the result for the three defined ML problems. Under this iterative training and evaluation process, the best performance is obtained with MI. Therefore, in Table III, we show in descending order the 14 most relevant features for predicting E_{SFN}, MER_{MFN}, and G_{SFN}.

Table III could be analyzed as a complement of the previously presented dataset correlation analysis. We can see how, for E_{SFN}, the two most important features are E_{MFN} and MER_{MFN}. Additionally, for MER_{SFN} the three most important features are E_{SFN}, E_{MFN} and MER_{MFN}. These results are in total accordance with the univariate distributions and pairwise relationships presented in Fig. 4. In the case of G_{SFN}, the two most important features are MER_{SFN} and MER_{MFN} in accordance with (1).

After the definition of the feature subset that better represents the labels in each ML problem, the dataset is split into the train (80 %) and test (20 %) data, guaranteeing to fit the ML algorithms and estimate their performance with different data. We apply Grid-search and k-fold cross-validation to evaluate all the possible combinations of hyperparameters that characterize the ML algorithms and fine-tune them. According to the reduced size of the dataset, we use k = 10, which offers the best tradeoff between bias and variance [27].

Finally, as an iterative process, the ML trained models are evaluated. If their performance is worse than the desired, we start the process again.

The performance evaluation process for the regression ML models is based on the R^2, MAE, and $RMSE$. The coefficient of determination is considered in [49] as a more intuitive metric to evaluate regression models. The R^2 metric is understood as a standardized version of the mean square error (MSE) or as the fraction of response variance that is captured by the model [43], defined as

$$R^2 = 1 - \frac{MSE}{Var(y)} = \frac{\frac{1}{N} \times \sum_{i=1}^{N}(y^{(i)} - \hat{y}^{(i)})^2}{\frac{1}{N} \times \sum_{i=1}^{N}(y^{(i)} - \mu_y)^2} \quad (2)$$

where $Var(y)$ is the variance of the expected values in the dataset (the label). The $y^{(i)}$ is an expected value, $\hat{y}^{(i)}$ is the corresponding predicted value, and N is the number of samples of the dataset. Whereas the expression $y^{(i)} - \hat{y}^{(i)}$ is the prediction error of the sample i ($error_i$). If $error_i$ is equal to zero for every i, the R^2 value is equal to one, which means that the model fits the data perfectly with an $MSE = 0$ [43].

The MAE represents the performance of the prediction model for each observation sample [16]. It measures the distance between two vectors: the vector of predictions and the vector of target values. The MAE does not characterize the type of errors but helps to weight the error magnitude. It is defined as

$$MAE = \frac{\sum_{i=1}^{N}|error_i|}{N}. \quad (3)$$

The $RMSE$ explains how large is the error that the system typically makes in its predictions [27]. It is defined as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(error_i)^2}{N}} \quad (4)$$

This metric punishes larger errors than smaller ones. It is important to highlight that the units of the $RMSE$ are the same as the original units of the predicted value.

On the other hand, we use the accuracy metric and the confusion matrix to analyze the performance of the classification ML algorithms. The former represents the ratio of correct predictions [50]. Whereas the latter counts the number of instances of class A classified as class B (e.g., the number of instances classified as '1' when there really are '0', which means false positive) [27].

C. Phase 3: ML Concatenated Structure

Table III shows that the most important feature to predict MER_{SFN} is the E_{SFN}. However, the goal of our proposal is to train the ML algorithms to be capable of predicting the SFN parameters from just the MFN and position data. The same happens for the classification into positive or negative SFN gain ($Gpclass_{SFN}$), the most important feature to predict it is the MER_{SFN}. This situation motivates the use of a concatenated structure of ML algorithms to take advantage of such correlations and improve the results.

The proposed ML concatenated structure is presented in Fig. 5. The letter "p" in the name of the variables is introduced to differentiate the predicted features from measured values for the same metric (e.g., Ep_{SFN} is the predicted feature and E_{SFN} is the measured one). The measured values are used for the training process, while the predicted values are used for the evaluation of the concatenated structure.

Ep_{SFN} is predicted only with MFN and position data parameters. The resulting Ep_{SFN}, the position and MFN data, are used as features to predict the $MERp_{SFN}$. We train the ML algorithms to predict the MER_{SFN} values by using the measured values of E_{SFN}, MFN and position data. In contrast, we use the Ep_{SFN} as input in the evaluation process.

As we previously define, to calculate the exact G_{SFN} value (Gp_{SFN}), we apply (1) with the predicted $MERp_{SFN}$ and the measured MER_{MFN}. Then, combining the previous stage of prediction, Ep_{SFN} and $MERp_{SFN}$ with the position and MFN data we predict the $Gpclass_{SFN}$. As in the previous case, we train the classification algorithms with the measured values of E_{SFN}, MER_{SFN}, MFN and position data.

IV. RESULTS

This section presents the results of the training phase for the individual algorithms and the performance analysis of the ML concatenated structure. The proposal is validated by comparing with the performance of the direct prediction of the SFN parameters, only using position and MFN parameters.

A. Results of ML Algorithms Training

Fig. 6, 7, and 8 show the results of the ML algorithms predicting E_{SFN} and MER_{MFN} in terms of R^2, and $Gclass_{SFN}$ in terms of accuracy. All the presented results are for the ML algorithms trained to use in the concatenated structure. The evaluated features are ordered according to the ranking presented in Table III.

Fig. 6 shows the results for predicting the E_{SFN} parameter applying the regression algorithms GB, RF, SVR, and MLP-R. The best performance is obtained by RF, which requires only the five most important features presented in Table III to
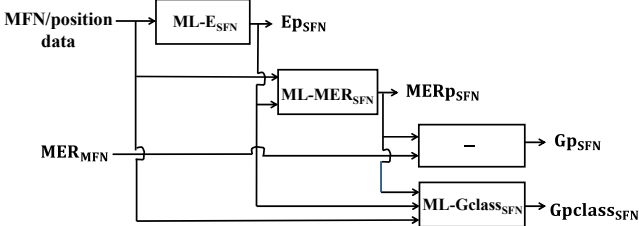

Fig. 5. ML concatenated structure (Phase 3).

achieve the best result $R^2 = 0.93$. A similar result is reached by the SVR algorithm, in this case with the six most important features. Fig. 6 shows that using more features does not imply better performance. Therefore, identifying the most important features has a relevant influence during the ML training process.

As Table III shows, the two most important features to predict E_{SFN} are the E_{MFN} and MER_{MFN} values of the MFN at each location. Nevertheless, features three, four, and five from Table III allow the algorithm to improve the R^2 value performance compared to when just using E_{MFN} and MER_{MFN} in the training process.

For MER_{SFN} (Fig. 7), the RF algorithm converges to the best result $R^2 = 0.983$ with the four most important features. In this case, the most important feature to predict the MER_{SFN} is the E_{SFN}, as we can see in Table III. Additionally, the R^2 values for RF, GB, SVR, and MLP range from 0.975 to 0.983, meaning that the contribution of the remaining features is significantly less critical. This result corroborates the strong correlation between E_{SFN} and MER_{SFN} presented in Fig. 4.

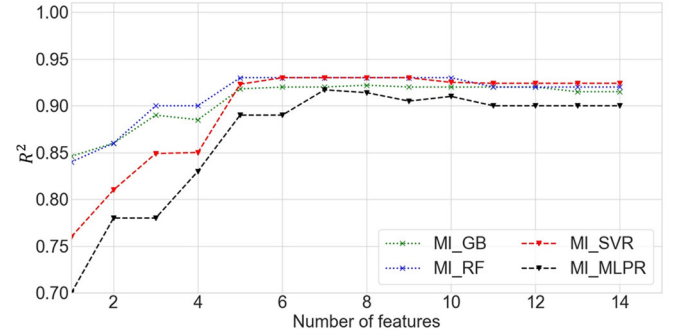Fig. 8 shows the results for $Gclass_{SFN}$ during the training and evaluation phase. In this case, the GBC and MLP-C

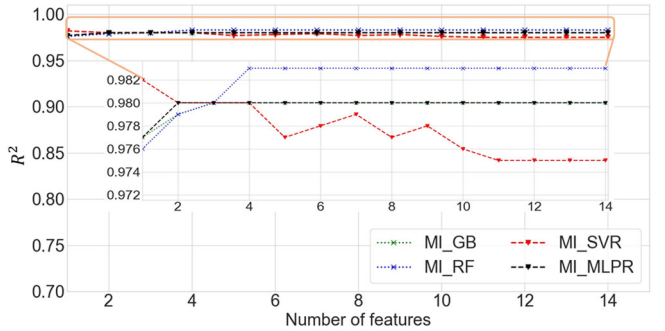Fig. 6. R^2 vs. number of features for E_{SFN}.

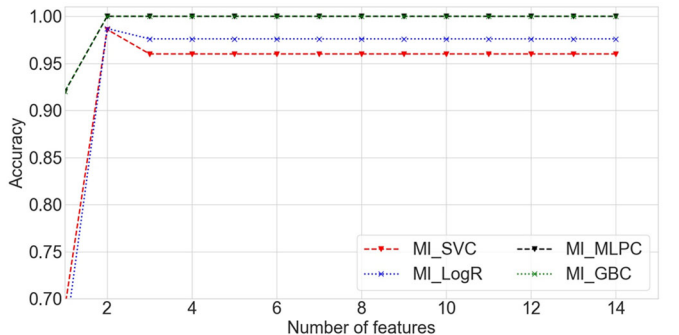Fig. 7. R^2 vs. number of features for MER_{SFN}.

Fig. 8. Accuracy vs. number of features for $Gclass_{SFN}$.

algorithms converge to a perfect accuracy equal to 1 with the two most important features (MER_{SFN} and MER_{MFN}). This result is logical and in total accordance with the linear relation of G_{SFN} value with MER_{SFN} and MER_{MFN} presented in (1).

B. Results of the ML Concatenated Structure

This subsection presents the results of the ML concatenated structure. As defined in section III, this work aims to predict the SFN performance only with the MFN and position data. Avoiding time-consuming and expensive measurements, the proposed ML concatenated structure allows predicting the SFN parameters E, MER, gain, and the classification of positive or negative gain. The results could help provide the desired QoS to end-users and exploit the advantages associated with the deployment of SFNs.

The prediction of the Ep_{SFN} value is only based on MFN and position data, as we defined in the previous section. The best ML algorithm to estimate the SFN E is RF with an $R^2 = 0.93$, a $MAE = 1.90$ dBμV/m, and an $RMSE = 2.76$ dBμV/m.

To predict $MERp_{SFN}$, we evaluate the proposal for all the combinations of supervised ML algorithms, presented in subsection III-B. Gp_{SFN} is then calculated as the difference between the most accurate $MERp_{SFN}$ prediction and the measured MER_{MFN}.

Table IV presents the four best combinations of applying the ML concatenated structure in terms of R^2, MAE, and $RMSE$. The combination of GB, GB with the subtraction operation has the best performance, estimating the MER with an $R^2 = 0.98$ and the SFN gain with an $R^2 = 0.89$. The concatenated structure outperforms the direct prediction of $MERp_{SFN}$ and Gp_{SFN} by 5 % and 44 %, respectively. The considerable difference between the concatenated ML structure and the direct prediction of G_{SFN} demonstrates the previously presented (subsections III-A and III-B) weak correlation of the SFN gain with just position and MFN parameters.

Table V shows the five best results predicting Ep_{SFN},

$MERp_{SFN}$ values, and $Gpclass_{SFN}$. In the case of the ML classification algorithms, the evaluation is expressed in terms of accuracy. The combination with the best performance is GB, GB, and GBC. It is possible to estimate the discretized gain values with an accuracy equal to 0.97. Comparing with the direct prediction, we highlight that our proposal improves the prediction of $Gpclass_{SFN}$ by 24 %.

Fig. 9 shows the confusion matrix resulting from the best ML concatenated structure to predict the discretized values of SFN gain (GB+GB+GBC). 47 % of the test points are true positives, and 48.3 % are true negatives. Moreover, only 3.1 % of the test data points are false positives, whereas 1.6 % are false negatives.

V. CONCLUSION

This paper presents an ML concatenated structure to predict the performance parameters: electric-field signal strength, modulation error ratio, and gain of an SFN from the legacy deployed MFN and position data. We train, concatenate, and evaluate several supervised regression and classification ML algorithms to maximize the prediction performance.

We apply several methods during the data preparation and the ML algorithms training, allowing us to drop the dataset outliers, and fine-tune the algorithms. We use feature importance and data correlation analysis to understand the existing pairwise relationships between the SFN and MFN
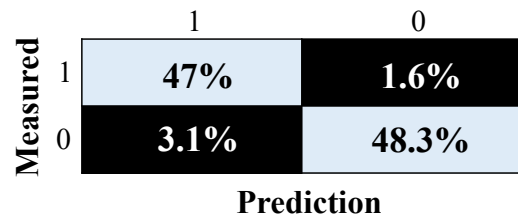

Fig. 9. Confusion matrix for the $Gpclass_{SFN}$ resulting from the best ML concatenated structure.

TABLE IV
SFN PREDICTION ERROR METRICS BY THE CONCATENATED STRUCTURE (REGRESSION ALGORITHMS) AND THE DIRECT PREDICTION

Variable	Error metrics	GB+GB+subtraction	GB+RF+subtraction	RF+GB+subtraction	RF+RF+subtraction	DP
Ep_{SFN}	R²	0.92	0.92	0.93	0.93	0.93
	MAE [dBμV/m]	2.10	2.10	1.90	1.90	1.98
	RMSE [dBμV/m]	2.98	2.98	2.76	2.76	2.8
$MERp_{SFN}$	R²	0.98	0.98	0.97	0.98	0.93
	MAE [dB]	0.54	0.61	0.80	0.72	1.57
	RMSE [dB]	1.03	1.03	1.11	1.02	2.13
Gp_{SFN}	R²	0.89	0.88	0.85	0.83	0.45
	MAE [dB]	0.53	0.63	0.80	0.88	1.78
	RMSE [dB]	1.00	1.01	1.16	1.23	2.29

TABLE V
SFN PREDICTION ERROR METRICS BY THE CONCATENATED STRUCTURE (REGRESSION AND CLASSIFICATION ALGORITHMS) AND THE DIRECT PREDICTION

Variable	Error metrics	GB+GB+GBC	RF+GB+GBC	GB+RF+GBC	RF+GB+LogR	MLP+MLP+MLPC	DP
Ep_{SFN}	R²	0.92	0.93	0.92	0.93	0.92	0.93
	MAE [dBμV/m]	2.10	1.90	2.10	1.90	1.96	1.98
	RMSE [dBμV/m]	2.98	2.76	2.98	2.76	2.7	2.8
$MERp_{SFN}$	R²	0.98	0.97	0.98	0.97	0.94	0.93
	MAE [dB]	0.54	0.80	0.61	0.67	0.66	1.57
	RMSE [dB]	1.03	1.11	1.03	1.09	1.9	2.13
$Gpclass_{SFN}$	Accuracy	0.97	0.95	0.94	0.93	0.88	0.73

parameters. These results show the main dependencies of the SFN labels and help to complement from a ML perspective the results presented in [19].

The two most important features to predict E_{SFN} are the E_{MFN} and MER_{MFN} parameters of the MFN at each location. The best ML algorithm to estimate the electric field strength is RF with an $R^2 = 0.93$, a $MAE = 1.90$ dBμV/m, and an $RMSE = 2.76$ dBμV/m. This result is obtained from only MFN and position data.

For MER_{SFN}, the most important features are the E_{SFN}, MER_{MFN}, and E_{MFN}. The best concatenated structure for the MER_{SFN} prediction is GB with GB, obtaining an $R^2 = 0.98$ dB, a $MAE = 0.54$ dB, and an $RMSE = 1.03$ dB.

To predict the SFN gain value, the best concatenated structure combines GB, GB, and the subtraction of the predicted $MERp_{SFN}$ with the measured MER_{MFN}, achieving an $R^2 = 0.89$, a $MAE = 0.53$ dB, and an $RMSE = 1.00$ dB. Furthermore, the best performance to estimate the discretized values of SFN gain is obtained with the ML concatenated structure GB, GB, and GBC. It is possible classifying into positive or negative the SFN gain at each dataset point with an accuracy of 0.97.

The results prove that the ML concatenated structure outperforms the direct prediction of the SFN parameters. In the case of the G_{SFN} value, the concatenated structure improves the results by 44 %. In the case of the $Gpclass_{SFN}$, the concatenated structure improves the results by 24 %.

The proposal could help to reduce the uncertainty of theoretical and empirical propagation models during the network planning and the long time and expensive measurements associated with the transition from an MFN to an SFN. Our proposal shows the feasibility of having a performance estimation of an SFN from collected data about the legacy deployed MFN and position data by using ML algorithms.

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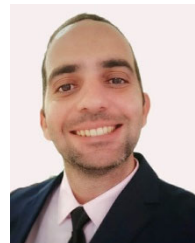
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