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Optimization of Electromagnetic Interference Measurement by Convolutional Neural Network

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***Abstract*—**With ever-increasing use of equipment, device or more generally any electrical or electronic system, the chance of Electromagnetic incompatibility incidents has considerably increased which demands more attention to ensure the possible risks of these technologies. Therefore, complying with certain Electromagnetic compatibility (EMC) rules and not overtaking an acceptable level of radiated emissions are utmost importance for the diffusion of electronic products. In this paper, developed measure tool and a convolutional neural network were used to propose a method to reduce the required time to carry out the final measurement phase of Electromagnetic interference (EMI) measurement according to the norm EN 55032 by predicting the radiated emission and determining the height of the antenna that meets the maximum radiation value.

***Keywords*—**Antenna height, Convolutional Neural Network, Electromagnetic Compatibility, Mean Absolute Error, position error.

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I. Introduction

WITH the exploding growth in use of electronic equipment in past decades, EMC issues have drawn great attention in science, engineering communities and, government agencies. EMC ensures equipment, device or more generally any electrical or electronic system functions satisfactorily in the presence of electromagnetic waves induced or generated by similar devices or natural causes in its vicinity [1], [2]. EMC also requires the device to properly work without introducing or generating unacceptable electromagnetic disturbance to other equipment in the environment. To confirm that the equipment and electrical or electronic systems are complying with standards, therefore emission and immunity tests have to be performed as described in norms.

Deep learning has emerged in the last few years as a premier technology for building intelligent systems that learn from data. Deep Neural Networks (DNN), originally roughly inspired by how the human brain learns, are trained with large amounts of data to solve complex tasks with unprecedented accuracy. DNN has been widely used in the field of electromagnetics. In [3], DNN uses the magnitude and phase information of the radiation field to perform near-field prediction at a single frequency. A new method for equivalent magnetic dipole prediction is established based on convolutional neural network proposed in [4].

EMI radiated emission measurements are often referred to the field strength value obtained at a given distance [5]. To perform EMI measurement, many environments could be used: semi-anechoic chamber (SAC), fully anechoic room (FAR), or reverberation chamber (RC) and even near-field scanning (NFS) technique. In our paper radiated emission tests are carried out in a 3 m SAC. These emission tests have some evident obstacles. To perform an EMI measurement, all EMI emission in any direction and for all possible test setups must be captured, therefore, one has to turn a turntable, change the antenna height, and measure in two polarizations. Furthermore, all the measurement equipment also has to follow requirements defined by CISPR 16-1 standard [6]. Therefore, the desired cost and the test time to measure the emission in SAC must be considered.

Several papers have been published on SAC measurements. In [7], an experimental analysis of radiated emission limits regarding test facilities according to EN 55032 [8] was performed. The characteristics of the two SACs below 30 MHz were measured using monopole and loop antennas to present a new method to evaluate the test sites for such EMI measurement [9].

In this paper, we propose a measurement method to lessen the requested test time to perform EMC radiated measurement in SAC below 1 GHz according to the EN 55032 Class B by using a DNN.

The rest of this paper is organized as follows: The performance of the electromagnetic measurement is discussed in Section II, in Section III, 1D convolution neural network is cleared. Sections IV and V explain the construction of the proposed 1D CNN and the implementation of the measurement method using different scenarios. In Section VI we verify our results by comparing them with the real measurements which were carried out in SAC. Finally, Section VII concludes the paper.

II. Electromagnetic Emission Measurement Performance According to EN 55032 in the Frequency Range 30 MHz to 1 GHz in SAC

Measurements are performed in Normalized Site Attenuation (NSA) compliant SAC according to EMC basic standard. The test site is compliant to CISPER 16-1-4:2010 [10] and ANSI C63.4:2009 chap 5.4.2 to 5.4.4 [11].

To carry out this measurement, two steps are required:

- Pre-measurement: The equipment under test (EUT) is set to perform in the worst-case operating mode. The test is done by variation of turntable positions, the Azimuth step of turntable is set to 90°, and for every position antenna is set to heights 1.0 m & 1.82 and two polarizations

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(Horizontal/Vertical). The tests are also carried out with Peak Detector (PK), repetitive scan and max-hold mode. The results are documented.

- Final measurement: The peak values show which were documented from the previous phase are not maximized and these values closer than 6 dB to the limit line are considered as critical frequencies. A maximum search is done with PK and Quasi-Peak CISPR QP detectors for the critical frequencies. First a frequency zoom within +/- 10*IF-BW of the critical frequency, then the EUT is rotated continuously and the antenna height changed between 1 m and 4 m in order to find the worst position. After defining the worst position, the final measurements with QP detector are carried out in this position and the final values are stored.

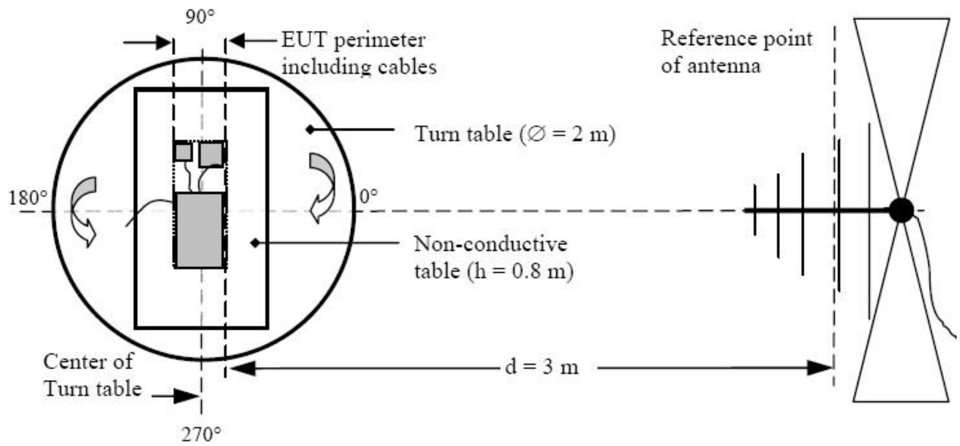

Fig. 1 The set-up of SAC for EMC radiated emission test under 1 GHz

The measurement distance is reduced from 10 m to 3 m and therefore an inverse proportionality factor of 20 dB per decade (according to CISPER 11 / to CISPER 22 /ANSI c63.4/VITR) is used. A transducer factor with -10.46 dB is used to normalize the measurement results to the specified distance (10 m).

According to EN 55032, the measurement procedure is performed using two phases.

III. 1D Convolutional Neural Networks

Convolutional Neural Network (CNN) consists of convolution layer, pooling layer and other hidden layers. It has the advantage of incomplete connection, relatively simple model structure and strong data features extraction ability. CNN has been applied to time series (a 1-D grid) and an image (a 2-D grid) [12]. 1D CNNs have been widely applied used for the optimal design of antennas [13], Signal Processing Applications [14] and other fields. 1D CNNs show many advantages:

- Complexity of a 1D CNN is significantly lower than the 2D CNN.
- Most 1D CNN applications used deep architectures (1-2 hidden CNN layers) with less than 10 k parameters whereas almost all 2D CNN applications have used these architectures with more than 1 M parameters. Obviously, networks with shallow architectures are much easier to train and implement.
- CNNs are well-suited for real-time and low-cost applications especially on mobile devices, because of their low computational requirements.

IV. Construction of the Proposed 1D CNN Model to Predict the Electromagnetic Radiation Emission in SAC According to EN 55032

We briefly introduced the stages to construct a 1D model to predict the electromagnetic radiation emission according to the norm EN 55033_Class B.

a. Dataset Source

To train our CNN, a dataset was derived from measurements using Rode & Schwarz EMC32 software in SAC by CETECOM GmbH in, Essen Germany as illustrated in Fig. 2. At first, the pre-measurement was performed, EUT is set under the worst case and sweeps are performed (varying turntable positions, heights and polarizations of antenna). After that, the final measurements were performed for the critical frequencies to determine the worst turntable (0°-359°) position and antenna height (1,05 m-3,59 m). We used these turntable sweep files for learning processing for our proposed measurement method using 1D CNN model.

The final dataset contains six features: EUT position angles, Radiation Level (dBm/uV), Antenna Polarization (H/V), EUT Polarization (H/V), Correlation Factor (dB) and critical frequency (MHz).

b. Data Processing

The following processing steps were needed before feeding up data to our CNN model:

- Data Interpolation

The Rode & Schwarz EMC32 software saves the sweep during the varying of antenna as file contains two columns of values, one for antenna position height and the other for the

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related electrical filed values. The turntable rotation step was not the same in every measurement, so we needed to interpolate the saved file data and resaved them as a sequence in range (3.59 m-1.05 m) with 2 cm step.

- Data Split

The dataset was blindly separated into three subsets: 70% for training, 10% for validation and 10% for testing the network. The dataset will not be shuffled before splitting to indemnify that loping off the data into windows of consecutive sample is still possible and to ensure that the validation -test result, being evaluated on dataset after the model was trained, are more realistic.

We divided the sequence into multiple input/output patterns called samples. The CNN model will learn a function that maps a sequence of past observation as input to an output observation.

- Data Normalization

Considering features of the collected data sets have different dimensions and unit, the original data should be normalized first to ensure that these features have the same order of magnitude. Normalization of the features has the additional benefit of improving the accuracy of the DNN model and accelerating its training process. It is done by subtracting the mean and dividing by the standard deviation of each feature. Only the training dataset should be used to computed the mean and standard deviation so that the models have no access to the values in validation and test set.

- Data Windowing

Windows of consecutive samples from the dataset will be used to get the predicted values. The main features of these windows are the width (sum of the input values (measured steps and label values (predicted steps)), in our case it is 128 steps, offset between them and which features used as inputs, labels or both. Every window will be split and converted to a window of inputs and a window of labels. Fig. 3 illustrates data windowing process.

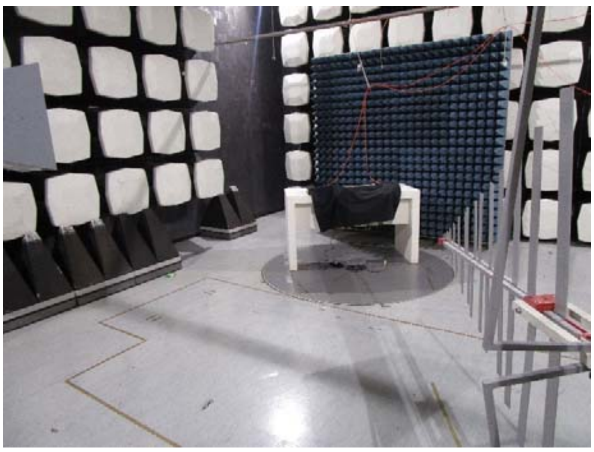

Fig. 2 The set-up of SAC for EMI radiated emission according to EN 55032 in Cetecom Essen, Germany

c. Training and Validation of the 1D CNN

The data in our dataset will be divided into standard single sequences. This sequence begins at High = 3,59 m and ends at 1.25 m. Every sequence will be transformed into input/output samples to train the model. The number of the steps as inputs will be the number we chose when we prepared our dataset according to certain scenarios. Our module was built depend on Multivariate Multi-step CNN model [15]. The architecture of the proposed model is depicted in Fig. 4.

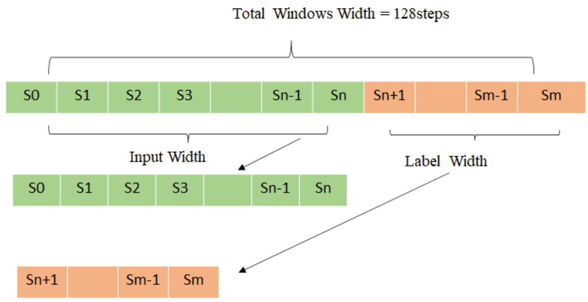

Fig. 3 Data Split to Input and Output (labels) to be used as learning data for Neural Network

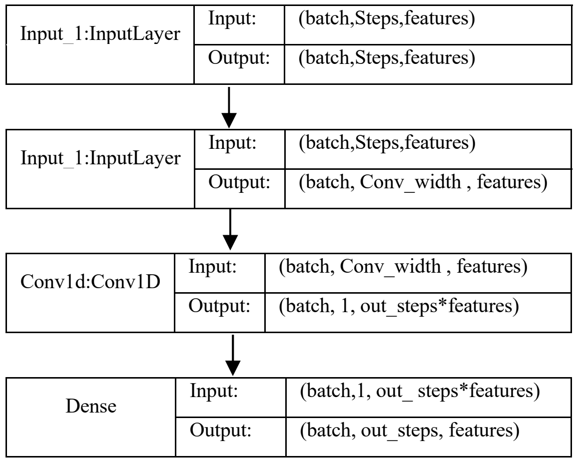

Fig. 4 The architecture of Multivariate Multi-step 1D CNN mode

The following parameters were used to train our module: Batch size = 128, convolution width = 3, features = 6, filters = 256, max_epoch =1000. We have used the Relu [16] as activation function. The mode was trained using different input/ output steps (Scenario1 (0.2 m, 3.39 m), Scenario2 (0.8 m, 2.79 m), Scenario3 (1.2 m, 2.39 m), Scenario4 (1.8 m, 1.79 m), Scenario5 (2 m, 1.59 m), Scenario6 (2.2 m, 1.39 m), as illustrated in Fig. 5 and saved separately.

Early stopping technique was used to avoid overfitting assuring better generalization performance. The Adam optimizer is demonstrated to have faster and more stable convergence in the training process, which also illustrates the best accuracy in this work.

The model was validated and evaluated with test data. Mean Absolute Error is selected as criterion for training and validation loss on our database. The form of MAE is [16]:

$$MEA = \frac{1}{n}\sum_i \mid Y_i - X_i \mid \qquad (1)$$

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Y_i and X_i represent the observed and predicted value for the i^{th} observation, n is the total number of observations.

Fig. 6 shows the training and validation results using scenario 1.

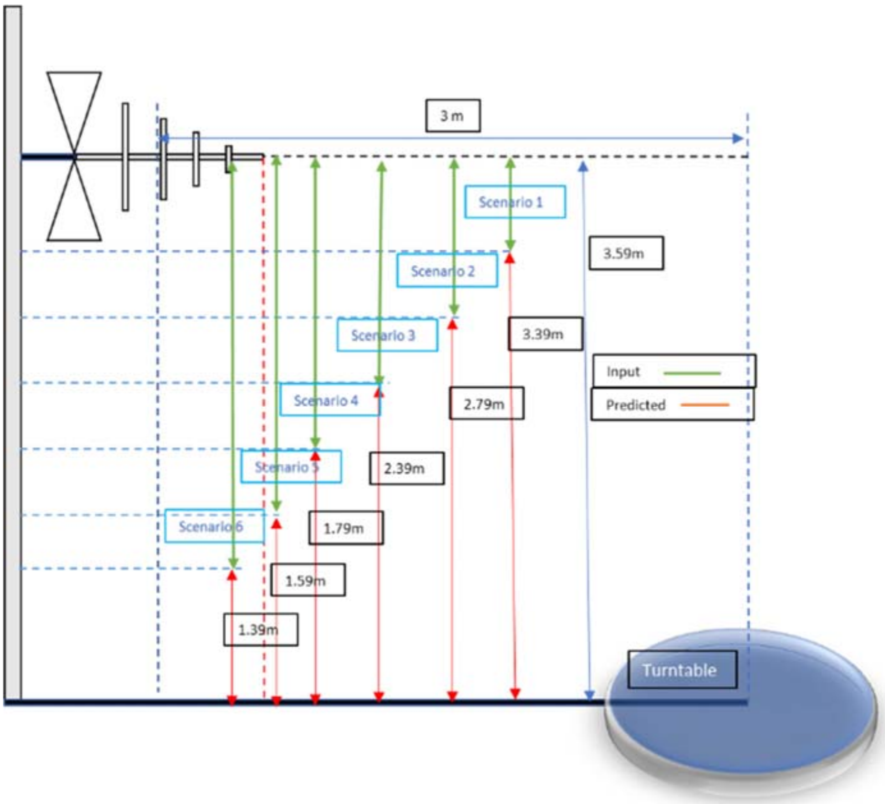

Fig. 5 Different Scenarios for Input/Output steps of Multivariate Multi-Stepp CNN mode

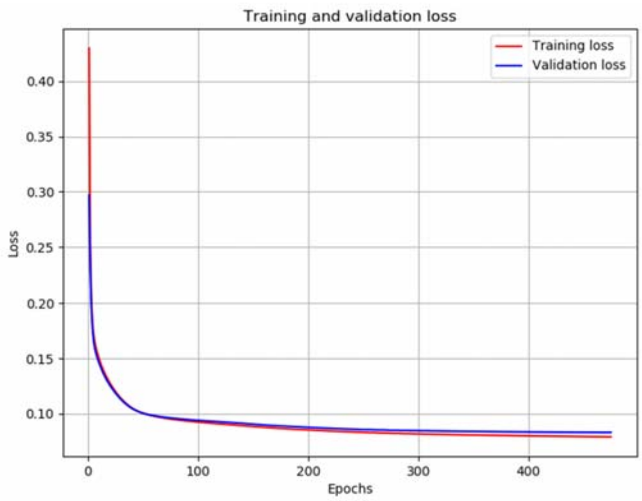

Fig. 6 Training and validation loss for our module using Scenario 1

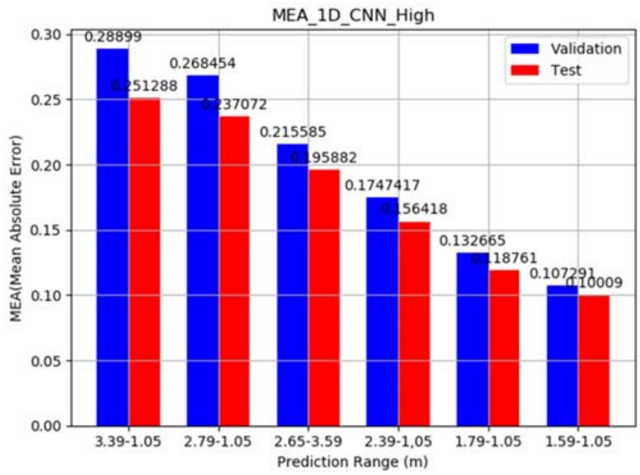

Fig. 7 The overall performance of the our 1D CNN module for different output ranges

As shown in Fig. 6, the training and validation losses start to diverge considerably after 120 epochs. The loss on the training dataset will always be lower than on the validation dataset.

Fig. 7 shows the overall performance of our module for different input scenarios.

V. Implementation of the Proposed Measurement Method

To discharge the proposed measurement method, a Python code was developed to carry out the performance EMI radiation measurements between 30 MHz and 1 GHz according to Norm EN 55032. Fig. 8 shows GUI for the developed software.

The software will implement maximum search with PK and

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Quasi-Peak CISPR QP detectors for the critical frequencies. After the setting of frequency zoom, then the angle of the maximum radiation will be found by rotate the turntable continuously in range (0°-359°).

After that, the second phase of final measurement must be started (varying antenna height). We observed from the training data that the maximal radiation height was always in range 1.05 m until 2.25 m; therefore, to make our proposed measurement method more effectively, the antenna height varying direction is reversed. Measurement result will be interpolated to 2 cm step and used with the Polarizations of EUT and antenna, critical frequency and the total attention at this frequency (the attention values tables were defined in our software) as inputs to our trained CNN model, which will predict the residual radiation values until 1.05 m and return the antenna height of the founded worth case (maximal radiation value). After defining the worst position, the final measurements with QP detector are carried out in this position and stored as a final result.

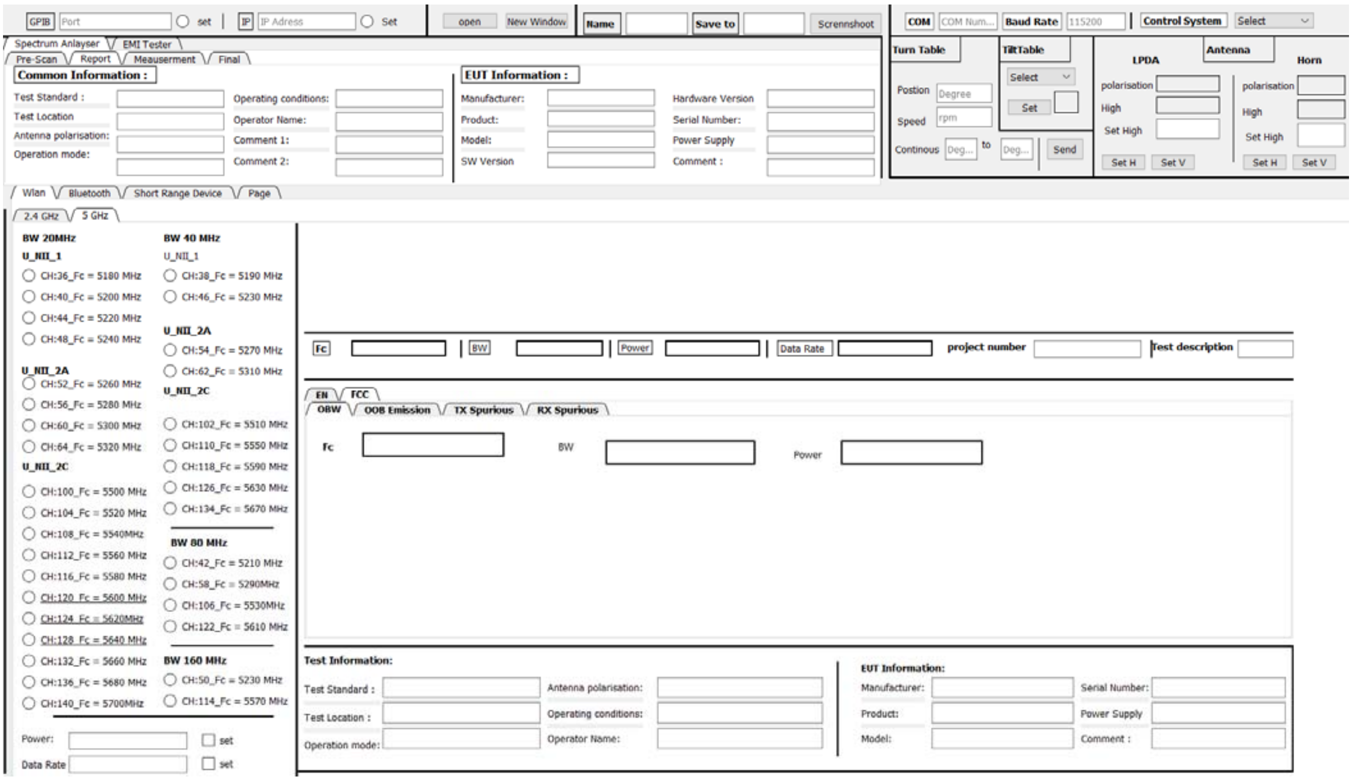

Fig. 8 GUI of our Software to performance our proposed measurement method and many EMC measurements

V. Performance and Efficiency Comparison of the Proposed Measurement Method

To verify our proposed measured method, a comparison between the predicted values from our 1D CNN model, and the target labelled values from final measurement process using Rode & Schwarz EMC32 Software was done. The final measurement values of the radiation during antenna variation for determined critical frequency acquired from our developed Software, EUT and antenna polarizations and the total transducer function were used as input to our module.

Different input scenarios (Fig. 5) were used to compare the worst case (maximal radiation) height position found by carrying out final measurements using proposed method with that one from measurements using Rode & Schwarz EMC32 Software.

Three EMI measurements for three different EUT were carried out using our developed software in SAC as shown in Fig. 9.

From each measurement, one critical frequency will be picked up, and the final measurement will be carried out. first the turntable should be turned in range (0° until 359°) to find the angle of the worst case (maximal radiation), then the turntable position will be switched to the position of the worth case. After that, the height of the antenna will be changed from 3.59 m until a certain high depended on our selected scenario (Fig. 5). These values, EUT and antenna polarizations were used as inputs for our proposed neural network model which predicted the residual values till 1.05 m, determined the worst-case height and returned it to our software to set the antenna at this position.

After the definition of worst-case position, the software carried out final measurements with QP detector and the final value is stored.

Table I illustrates the additional input parameters for the tested seven scenarios which will be fed in addition to the radiation measured value in a certain angle range to our neural network.

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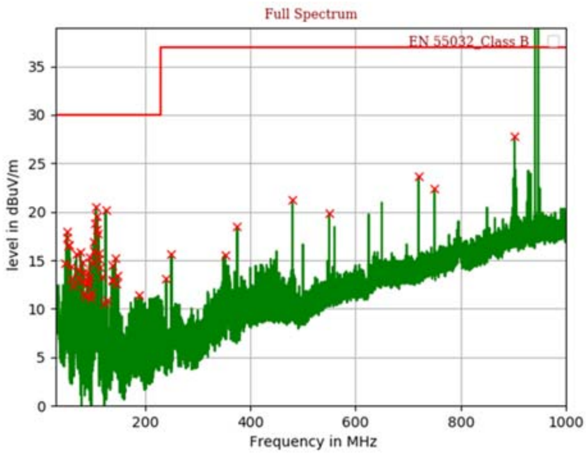
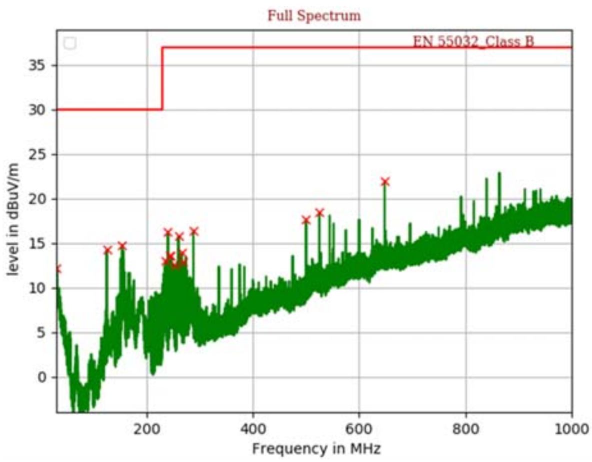
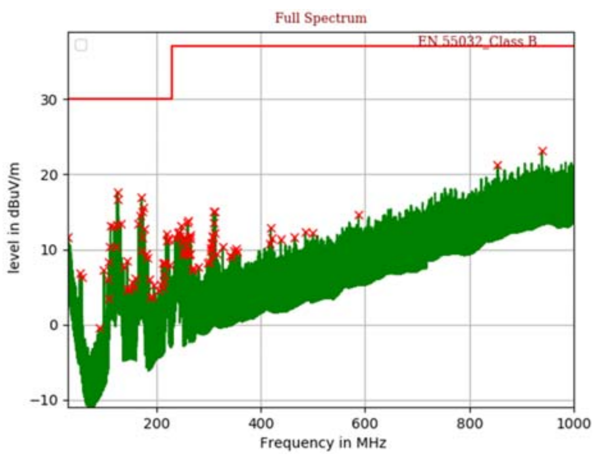


(a)



(b)



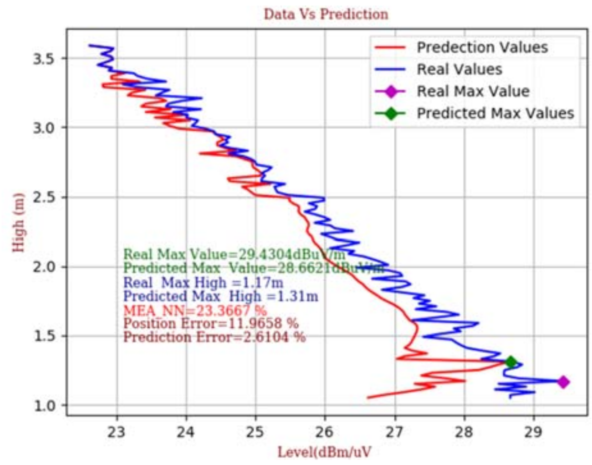
(c)

Fig. 9 EMI measurement results for three different EUTs in SAC, Cetecom GmbH Essen, Germany

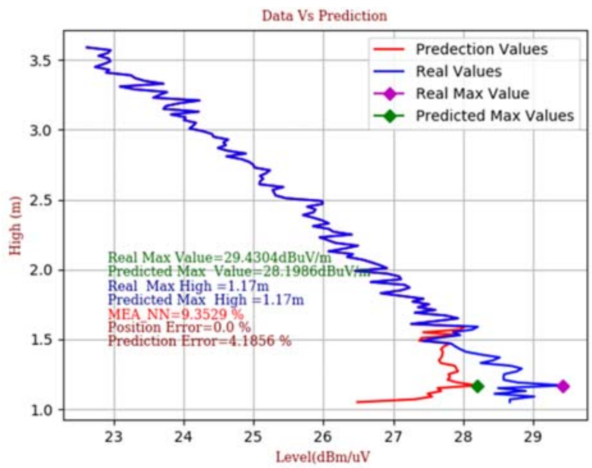
A comparison between the radiation values measured by complete variation of antenna height using Rode &Schwarz software and the predicted radiation values from our CNN is accomplished. The blue line represents the measured values (taken from EMC software by this example and will be exported from our software by the future EMI measurements) which we used as Input to our CNN in addition to other inputs from Table I. The length of this input sequence variance depended on the tested scenario; red line represents the predicted values. Real and predicted maximal radiation values and position, as well as the position and level errors for the final measurement result are illustrated in Figs. 10-12.

TABLE I
THE CHOSEN CRITICAL FREQUENCIES FROM THE EMI MEASUREMENTS IN SAC

Measurement	Critical Frequency	EUT Polarization	Antenna Polarization	Transducer factor (dB)
measurement 1	124.99	H	V	1.98
measurement 2	648.01	H	H	12.7
measurement 3	124.8	H	V	1.91



(a)



(b)

Fig. 10 Position and radiation level errors of predicted high and radiation level for critical frequency 124.99 MHz: (a) senario1 and (b) scenario 7

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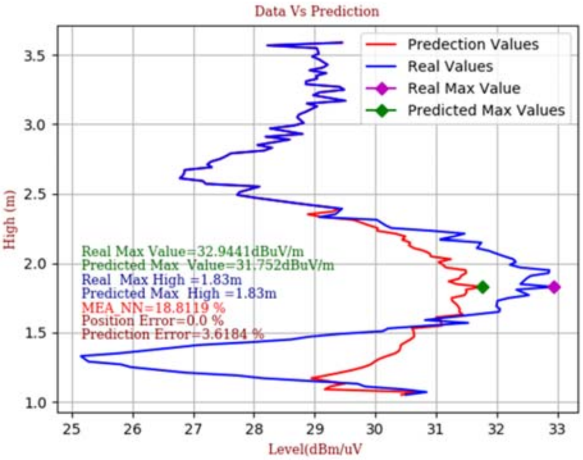
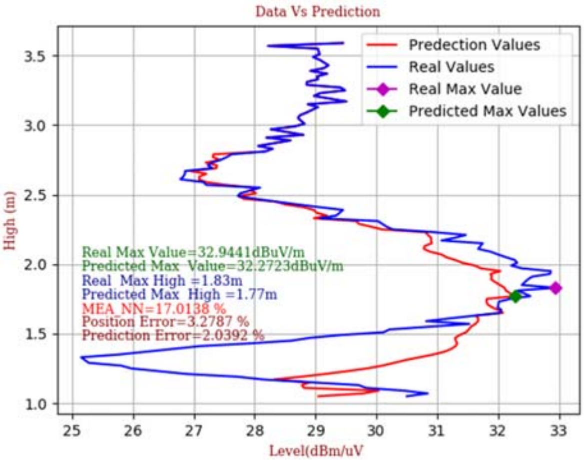
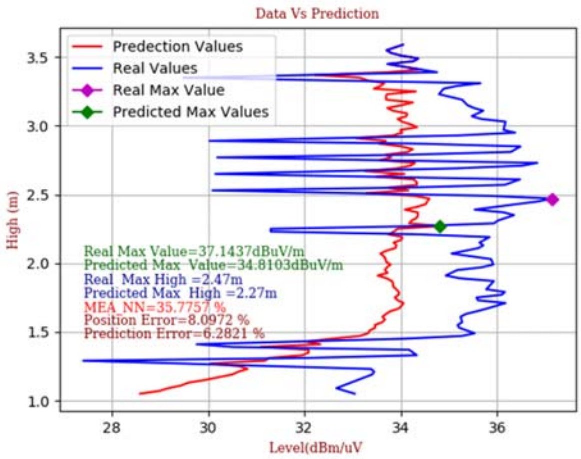


(a)

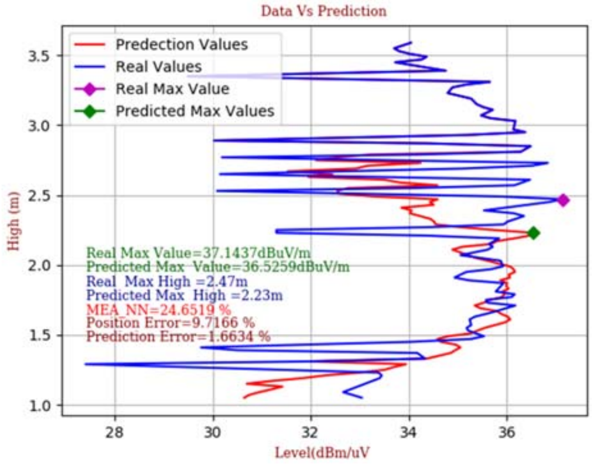


(b)

Fig. 11 Position and radiation level errors of predicted high and radiation level for critical frequency 648.01 MHz: (a) senario2 and (b) scenario 3



(a)



(b)

Fig. 12 Position and radiation level errors of predicted high and radiation level for critical frequency 124.8 MHz: (a) senario1 and (b) scenario 2

From Figs. 11 and 12, an obvious variation with radiation level is noticed. The reason for that is the EUT operating modes. We can remark the impact of the outliner filter during learning process for CNN.

Table II-IV show the position and radiation level errors of predicted height and radiation level for the critical frequencies.

By comparing real und predicted radiation levels in Figs. 10-12, Table II-IV, it can be seen that the height position and radiation value predicting errors are very small. Fig. 13 shows the saved time and the expected position error for the tested scenarios to determine the height of the antenna according to the maximal radiation point.

TABLE II
HEIGHT, RADIATION LEVEL AND MEAN ABSOLUTE ERRORS FOR THE FIRST MEASUREMENT

Scenario	Predicted Height	Predicted radiation level dBmuV/m	Position Error	Radiation Level Error	MEA
1	1.31m	28.6621	11.96%	2.6104%	23.366%
2	1.21m	28.4228	3.41%	2.6404%	22.772%
3	1.13m	28.4994	3.1633%	3.4188%	16.082%
4	1.17m	28.0653	0%	4.6384%	10.932%
5	1.17m	28.1986	0%	4.1856%	9.3529%
6	1.17m	28.3458	0%	3.6861%	9.2452%

f = 124.99 MHz, Real antenna hight = 1.17 m, real radiation level = 29.4304 dbuv\m

TABLE III
HEIGHT, RADIATION LEVEL AND MEAN ABSOLUTE ERRORS FOR THE SECOND MEASUREMENT

Scenario	Predicted Height	Predicted radiation level dBmuV/m	Position Error	Radiation Level Error	MEA
1	1.93m	31.7398	5.4645%	3.6556%	20.426%
2	1.77m	32.2723	3.2787%	2.0392%	17.013%
3	1.83m	31.752	0%	3.6184%	18.811%
4	1.83m	32.9441	0%	0%	14.894%
5	1.83m	32.9441	0%	0%	17.394%
6	1.83m	32.9441	0%	0%	7.2.38%

f = 648.01 MHz, Real antenna heigh = 1.83 m, real radiation level = 32.9441 dbuv\m

TABLE IV
HEIGHT, RADIATION LEVEL AND MEAN ABSOLUTE ERRORS FOR THE THIRD MEASUREMENT

Scenario	Predicted Height	Predicted radiation level dBmuV/m	Position Error	Radiation Level Error	MEA
1	2.27m	34.8103	8.0972%	6.2821%	35.775%
2	2.23m	36.5259	9.7166%	1.6634%	24.651%
3	2.47m	37.1437	0%	0%	20.875%
4	2.47m	37.1437	0%	0%	23.564%
5	2.47m	37.1437	0%	0%	17.142%
6	2.47m	37.1437	0%	0%	14.922%

f = 124.8 MHz, Real antenna hight = 2.47 m, real radiation level = 37.1437 dbuv\m

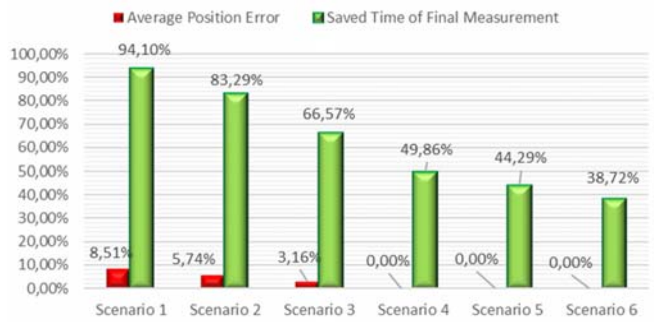


Fig. 13 Average position Error/Saved time of final measurement of six scenarios

The results indicate that with approximately 9% error on the position prediction, 94% from the required time to find the high of the antenna according to worth position is saved, and this time saving can be very effective especially in case of many critical frequencies.

VI. CONCLUSION

In this paper, a measuring method was introduced to speed up the final measurement process by predicting the radiation emission during the variation of the height of the antenna and determining the maximum radiated emission position using 1D CNN. Firstly, a python tool was developed to carry out the EMI measurement, according to EN55032 in this paper, then data taken from real measurements (performed in SAC by Cetecom GmbH, Essen, Germany) were used to build up a dataset and used it to train our 1D CNN. Our model was validated and evaluated with test data for six scenarios and mean absolute error was calculated for each scenario. To verify our proposed our method, three EMI measurements were compared with the predicted values from our CNN and the predicted height of the worst case with the measured values from R&S EMC32 software. The comparison results show that the prediction performance of the proposed measured method could be successfully applied to reduce the required time to find the height position of the maximal radiation produced from the EUT. This method can save costs and also provides an option for solving problem of the long required time to complete the final measurement phase by EMI test.

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