Electromagnetic Interference Radiation Prediction and Final Measurement Process Optimization by Neural Network

Hussam Elias, Ninovic Perez, Holger Hirsch

Abstract**—**The completion of the EMC regulations worldwide is growing steadily as the usage of electronics in our daily lives is increasing more than ever. In this paper, we present a method to perform the final phase of Electromagnetic Compatibility (EMC) measurement and to reduce the required test time according to the norm EN 55032 by using a developed tool and the Conventional Neural Network (CNN). The neural network was trained using real EMC measurements which were performed in the Semi Anechoic Chamber (SAC) by CETECOM GmbH in Essen Germany. To implement our proposed method, we wrote software to perform the radiated electromagnetic interference (EMI) measurements and use the CNN to predict and determine the position of the turntable that meet the maximum radiation value.

Keywords**—**Conventional neural network, electromagnetic compatibility measurement, mean absolute error, position error.

I. Introduction

IN the past few years, there is a growing interest in Artificial Neural Networks (ANN). The ANN has its own advantages, such as fast running speed, efficiency and the nature of black box. At the application level, ANN methods and one part of its broader family, deep learning (DL), have been applied to data processing, image classification, speech processing and other information processing task. Very recently, DL has been further extended to complex electromagnetic problems. In the field of antenna design and application, DL has been vastly used for the optimal design of antennas [1], [2]. In [3], a DL model was used to predict the base stations (BS) beamforming vectors directly from the signals received at the distributed BSs using only omni or quasi-omni beam patterns.

Recently, an innovative method based on ANN provides an alternative approach for radiation emission or EMI. In [4], Deep Neural Network (DNN) was used for the optimization of 3D integrated circuits and systems. In [5] the artificial network was used to predict the maximum radiated emission from printed circuit boards (PCB).

The number of electromagnetic emission sources are increasing by the increasing of clock frequency and integration density of electronic products in everyday life. These sources are becoming more compound, and in many cases, the products emit a lot of unwanted signals to another. Moreover, the increasing complexity of the electromagnetic emission environment is also caused by electronic devices that are evolving towards higher frequencies, smaller designs with limited electromagnetic emissions in measurements and lower power levels of operation.

Any product on the market which uses electronic circuitry must comply with EMC requirements. To meet EMC requirements the product must be tested for conducted and radiated emissions. The radiated emission tests are carried out in a 3 m or 10 m semi-anechoic chamber.

There are some noticeable drawbacks of the conventional SAC EMC technique:

- It is time-consuming for EMC radiated testing. In order to be able to capture EMI emission in any direction and for all possible test setups, 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].
- The cost and the test time which are a big problem when we want to measure the emission in SAC.

In this paper, a measurement method is proposed to reduce the requested test time to perform EMI radiated measurement in SAC below 1 GHz by using a DNN.

The rest of this paper is organized as follows: in Section II, the performance of the electromagnetic measurement is discussed, the 1D convolution neural network is cleared in Section III, while Sections IV and V explain the construction of the proposed 1D CNN and the implementation of the measurement method. In Section VI we compare our results with the real measurements done in SAC. Finally, Section VII concludes the paper.

II. Electromagnetic Emission Measurement Performance in SAC

Measurements between 30 MHz and 1 GHz are performed in a Normalized Site Attenuation (NSA) compliant SAC according to the EMC basic standard. The test site is compliant to CISPER 16-1-4:2010 and ANSI C63.4:2009 chap 5.4.2 to 5.4.4 [7].

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).

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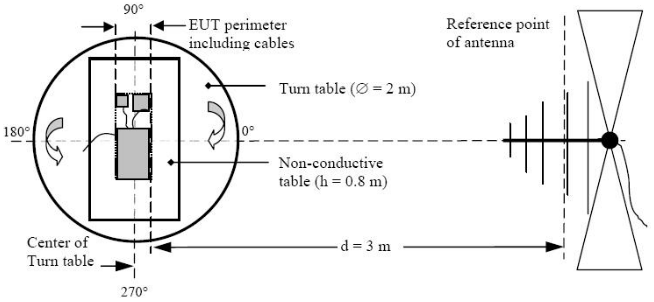


Fig. 1 The set-up of SAC for EMC radiated emission test under 1 GHz

To perform the measurement procedure two steps are needed:

- Pre-measurement: The equipment under test (EUT) is set in the worst-case operating mode determined. The test is done by variation of turntable positions, the Azimuth step of the turntable is set to 90°, and for every position the antenna is set to heights (1.05 m and 1.82 m) and two polarizations (horizontal/vertical). The tests are also carried out with peak detector (PK), repetitive scan and max-hold mode. The results are documented and the peak values are not maximized and these values closer than 6 dB to the limit line are considered as critical frequencies. If no critical frequencies are found (margin to limit less than 6 dB), the final measurement will be omitted.
- Final measurement: 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 is performed, then the EUT is rotated continuously and the antenna height will be changed between 1 m and 4 m in order to find the worst position. After defining the worth position, final measurements with QP detector are carried out in this position and the values are stored.

III. 1D Convolutional Neural Networks

The Convolutional Neural Network (CNN) was firstly introduced in [8]. It consists of a convolution layer, pooling layer and another hidden layer. It has the advantage of incomplete connection, relatively simple model structure and strong data features extraction ability. CNNs have been widely applied in pattern recognition sample classification, prediction and other fields. They are designed to operate exclusively on 2D data such as images and videos. This is why they are mostly referred as '2D' CNNs. Recently, a modified version of 2D CNNs have been developed and called 1D convolutional neural networks (1D CNN) [10], [11]. 1D CNNs show many advantages to 2D CNNs.

- Under the equivalent conditions, the computational complexity of a 1D CNN is significantly lower than the 2D CNN.
- Most 1D CNN applications use compact (with 1-2 hidden CNN Layers) configurations with networks that have less than 10 k parameters whereas almost all 2D CNN applications have used deep architectures with more than 1 M parameters. Obviously, networks with shallow architectures are much easier to train and implement.
- Because of their low computational requirements, 1D CNNs are well-suited for real-time and low-cost applications, especially on a mobile device.

The 1D CNNs have demonstrated a superior performance on those application that have a limited labeled data and high signal variation acquired from different sources.

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

We briefly introduced the stags to build a 1D model to predict the electromagnetic radiation emission according to the norm EN 55032_Class B [9].

a. Dataset Source

In this paper, we used a dataset derived from the final measurements, these measurements were done using Rode & Schwarz EMC32 software in SAC by CETECOM GmbH in Essen, Germany as illustrated in Fig. 2. The EUT does not have a big difference in size or volume. At first, the pre-measurement was performed, EUT is set under the worst case and 16 sweeps (4 turntable positions, 2 heights and 2 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 mode.

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

Firstly, it is necessary to understand the data before beginning the build of the proposed NN module. Next, it is important to be sure that the model is being passed appropriately formatted data. To do this, a few processing steps are needed before feeding data to the CNN model:

Data Interpolation

The Rode & Schwarz EMC32 software saves the sweep values for the variation of turntable positions as RESULT File (Result). These saved files contain two columns of values, one for turntable position angles and the other for the related electrical field values. The turntable rotation step was not the same at every measurement, so we needed to interpolate the saved file data and resave them as a sequence in range (0°-359°) with 1-degree rotation step.

Data Split

As typically recommended, the dataset was blindly separated into three subsets as follows: 70% for training, 15% for validation and 15% for testing the network. The dataset will not be shuffled before splitting to indemnify that loping off the data into windows of consecutive samples is still possible and to ensure that the validation-test results, being evaluated on the 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 observations as input to an output observation.

Data Normalization

Considering that features of the collected data sets have different dimensions and units, 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 compute the mean and standard deviation so that the models have no access to the values in the 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 is 360 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 the data windowing process.

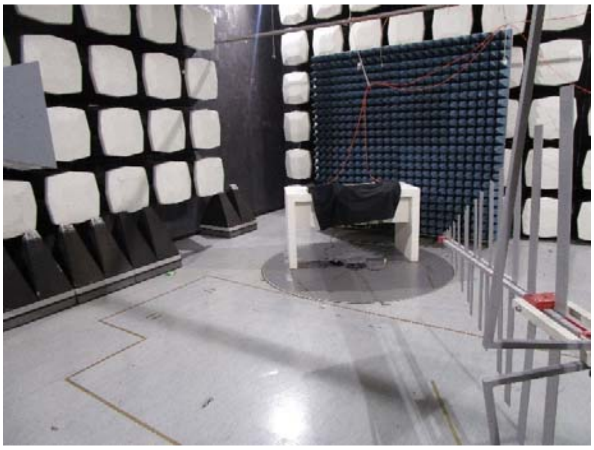


Fig. 2 The set-up of SAC for EMI radiated emission according to EN 55032 in Cetecom Essen, Germany

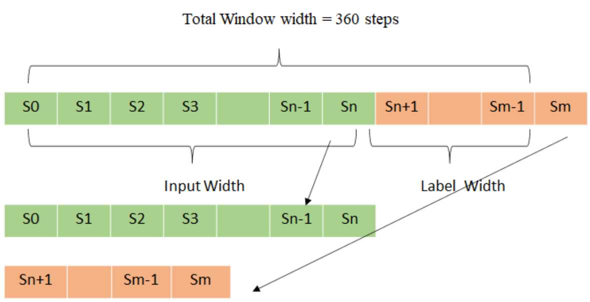


Fig. 3 Data Split to Input and Output (labels) to be used as learning data for Neural Network

c. Training and Validation of the 1D CNN

The data in our dataset will be divided into standard single sequences. This sequence begins at angle = 0° and ends at 359°. 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. Our module was built depending on the Multivariate Multi-step CNN model [12]. The architecture of the model is depicted in Fig. 4.

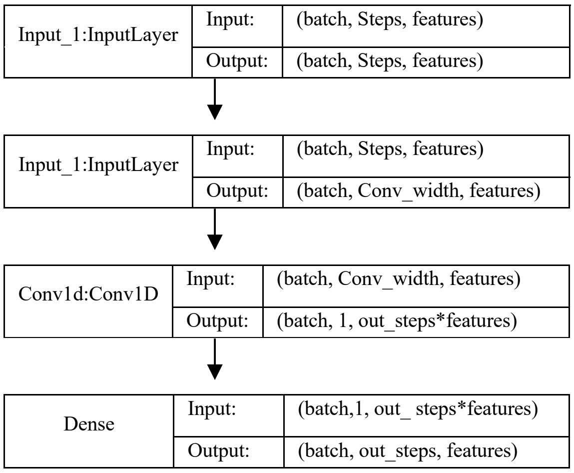


Fig. 4 The architecture of Multivariate Multi-step 1D CNN mode

We used the following parameters to train our module: Node number = 32, batch size = 360, convolution width = 3, features = 6, filters = 256, max_epoch =300. We have used the Relu [13] as activation function.

The model was trained using different input/output steps ((45°, 315°), (90°, 270°), (135°, 125°), (180°, 180°), (225°, 135°), (270°, 90°), (315°, 45°)) and saved separately. Fig. 5 illustrated the different scenarios used to train our 1D CNN.

Early stopping technique was used to avoid overfitting and assuring better generalization performance. Inter Quartile Range (IQR) approach filter was used to find the outliers in the training database, then they were removed from the database and replaced with the mean of the before and next values. 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 criteria for training and validation loss on our database. The form of MAE is as below [14]:

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

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 for scenario 7.

From Fig. 6, it is evident from the training and validation curves that the model is overfitting. The training and validation losses start to diverge considerably after 100 epochs. The loss of the model will almost always be lower on the training dataset than the validation dataset. This means that we should expect some gap between the train and validation loss learning curves and that because of the applying outliner filter on train data.

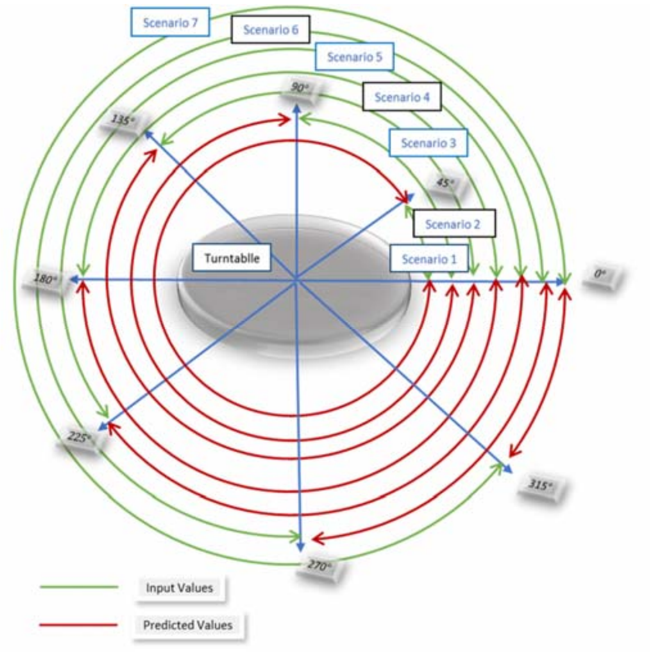


Fig. 5 Different scenarios for Input/Output steps of Multivariate Multi-step CNN mode

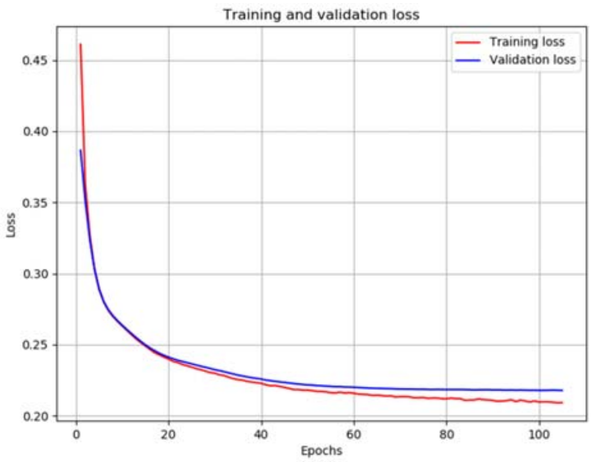


Fig. 6 Training and validation loss for input sequence (0°-315°)

The overall performance of our module for different output range is illustrated by Fig. 7.

V. Construction of the Proposed 1D CNN Model to Predict the Electromagnetic Radiation Emission in SAC

To implement our proposed measurement method, we developed a software to perform EMI radiation measurements between 30 MHz and 1 GHz as shown in Fig. 8. This software had been written with Python. It measures the EMI radiation according to Norm EN 55032. After EUT is set in the worst-case operating mode, pre-measurement will be done. By setting the turntable at four different azimuths and the antenna at two heights. The software will consider that values closer than 6 dB to the limit line are critical frequencies.

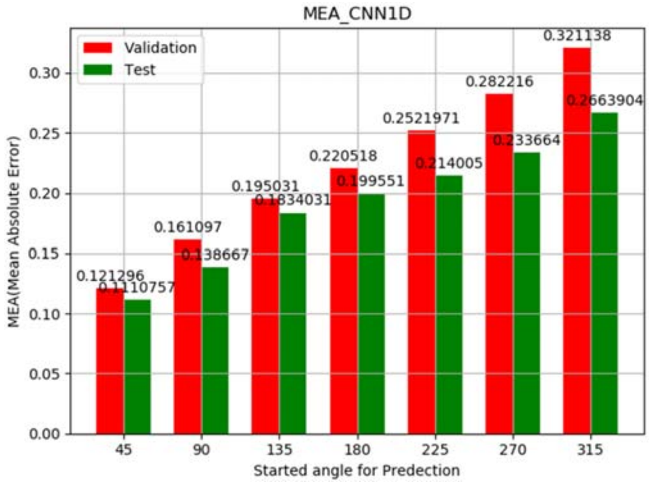


Fig. 7 The overall performance of the our 1D CNN module for different input ranges

The software will implement maximum search with PK and Quasi-Peak CISPR QP detectors for the critical frequencies. After the setting of frequency zoom, then the software will measure the radiation by rotate the turntable continuously until certain angle depends on chosen scenario configuration.

Measurement result will be interpolated to 1° 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 359° and returns the turntable position of the founded worth case (maximal radiation value). After that, the antenna height changed between 1.05 m and 3.59 m (the setting for SAC in Cetecom, Essen) in order to find the height of the worst position. After defining the worst position, the final measurement with QP detector is carried out in this position and the value is stored as a final result.

IV. Performance and Efficiency Comparison

With the aim to verify the proposed measurement method, we compare the predicted results calculated from our software using 1D CNN model, and the target labeled results from Rode & Schwarz EMC32 software. The final measurement values of the radiation during the continuous rotation of the turntable for determining critical frequency acquired from our developed Software, EUT, antenna polarization and the total transducer function were used as input to our module. We used seven different scenarios by using seven different inputs to predict the radiation values and find the maximum radiation position (worth case position). The input data will be first interpolated and processed, after that will be sent to 1D CNN module to get the predicted values. These values will compare with the values from EMC32 software.

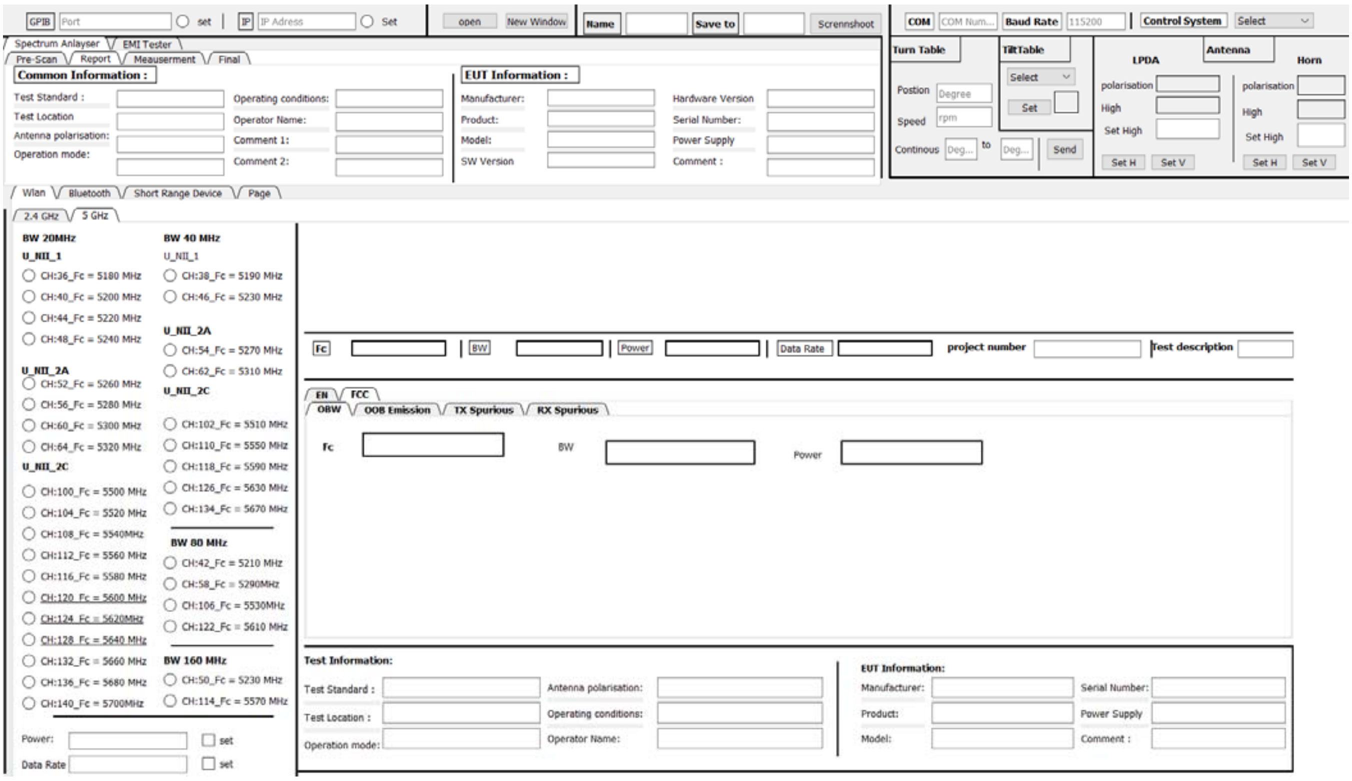


Fig. 8 GUI of our software to performance our proposed measurement method and many EMC measurements

Fig. 9 exhibits three EMI measurements for three different EUTS were carried out using our developed software in SAC. We picked up one critical frequency from each of them, the final measurement is carried out by our developed software as described in EN 55032 in a certain range depending on the selected scenario and used these values, critical frequency, EUT and antenna polarizations, will be used as inputs for our proposed neural network model which predicted the residual radiation values till 359°, to find turntable angle for the maximal radiation level and returned this position to our EMC software to set the turntable at this predicted position. Table I illustrates the inputs parameters for the tested seven scenarios which will be fed in addition to the radiation measured value in certain angles range to our neural network.

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

Measurement	Critical Frequency MHz	EUT Polarization	Antenna Polarization	Transducer factor (dB)
measurement 1	124.99	H	V	1.98
measurement 2	115.68	V	V	1.9
measurement 3	648.01	H	H	12.7

Figs. 10-12 compare the radiation values measured by complete variation of turntable positions using Rode & Schwarz software with the predicted radiation values from our CNN. The blue points represent the measured values that we used as an Input to our CNN in addition to other inputs from Table I. The length of this input sequence variance depended on the selected tested scenario, red points are the predicted values and the green points represent the residual radiation values from EMC software which will be compared with our CNN outputs:

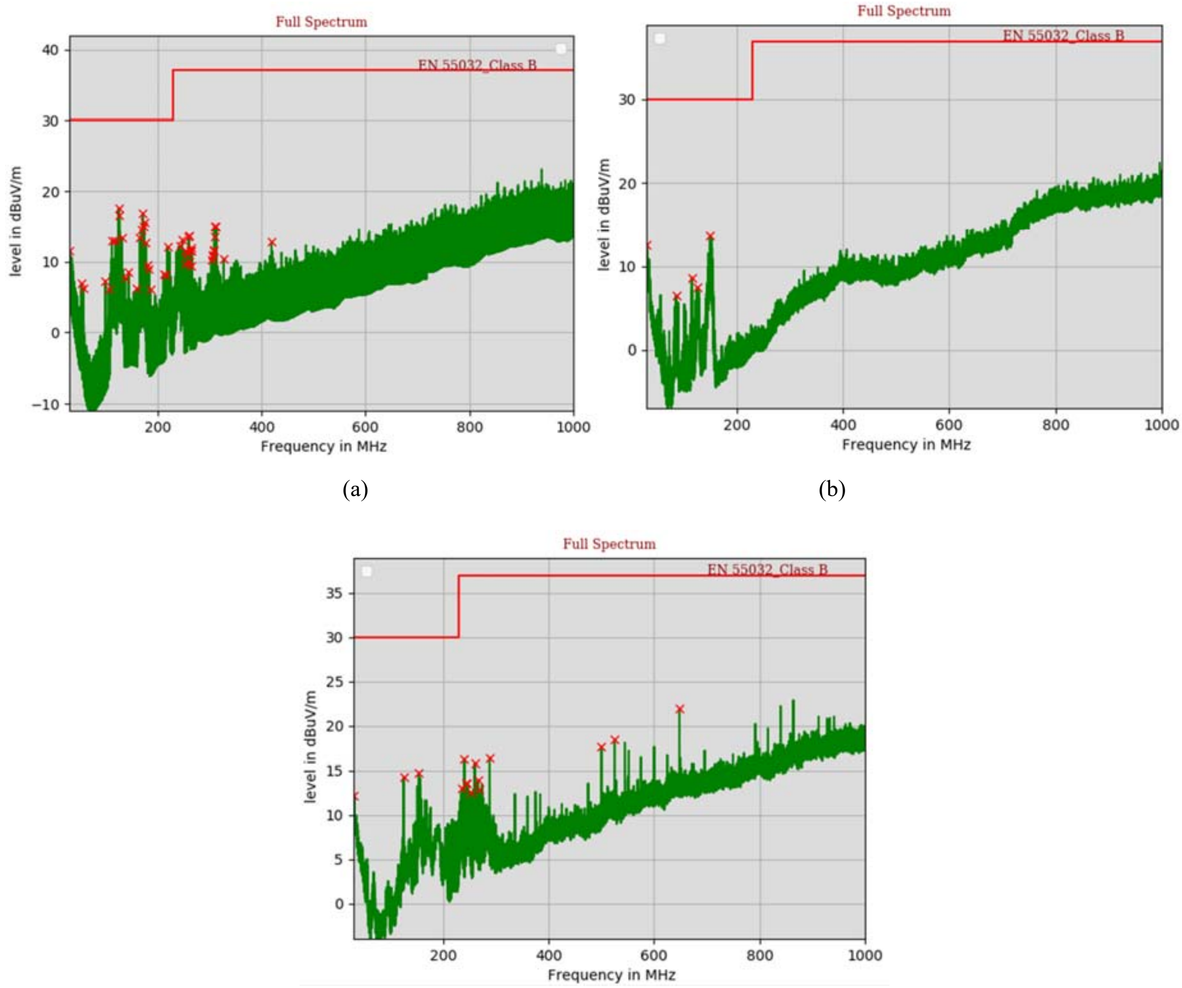
The turntable position correspondent to the maximal radiation value was determined for the exhibit and predicted radiation values for the picked critical frequencies, then position and radiation level errors were calculated.

From Fig. 11, we can see that the predicted values in the range above 270° are clearly different from the real ones, and due to the outliner filter, we used it by preparation data to be used for the neural network learning process. After that, the height of the antenna is changed in a set range (1.05 m till 3.59 m) to find the height corresponding to the maximal radiation.

Tables II-IV show the position and radiation level errors of predicted angel, while the radiation level for the critical frequencies is shown in Table I for the different scenarios.

TABLE II
POSITION, RADIATION LEVEL AND MEAN ABSOLUTE ERRORS FOR THE FIRST CHOSEN CRITICAL FREQUENCY TO DEFINE THE POSITION OF MAX RADIATION (F = 124.99 MHZ, REAL TURNTABLE ANGLE = 201°, REAL RADIATION LEVEL = 28.8449 DBUV\M)

Scenario	Predicated Angle (Position of max Radiation) (degree)	Predicated radiation level dBmuV/m	Position Error	Radiation Level Error	MEA
1	184	27.7048	8.4577%	4.1335%	30.774%
2	223	28.939	10.953%	0.137%	30.212%
3	213	28.3142	5.9701%	2.025%	32.151%
4	201	28.8944	0%	0.0291%	25.801%
5	201	0%	0%	0%	28.955%
6	201	0%	0%	0%	21.308%
7	201	0%	0%	0%	2.019%

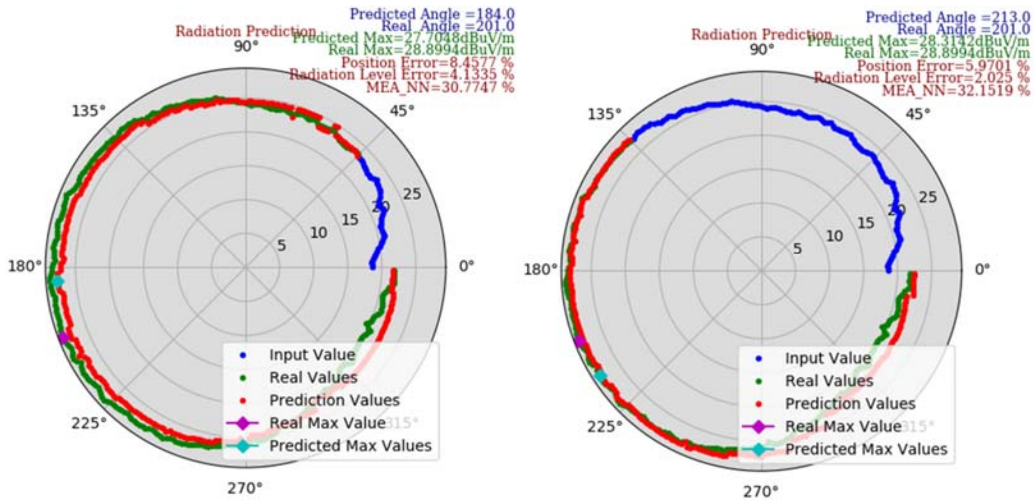


(a)

(b)

(c)

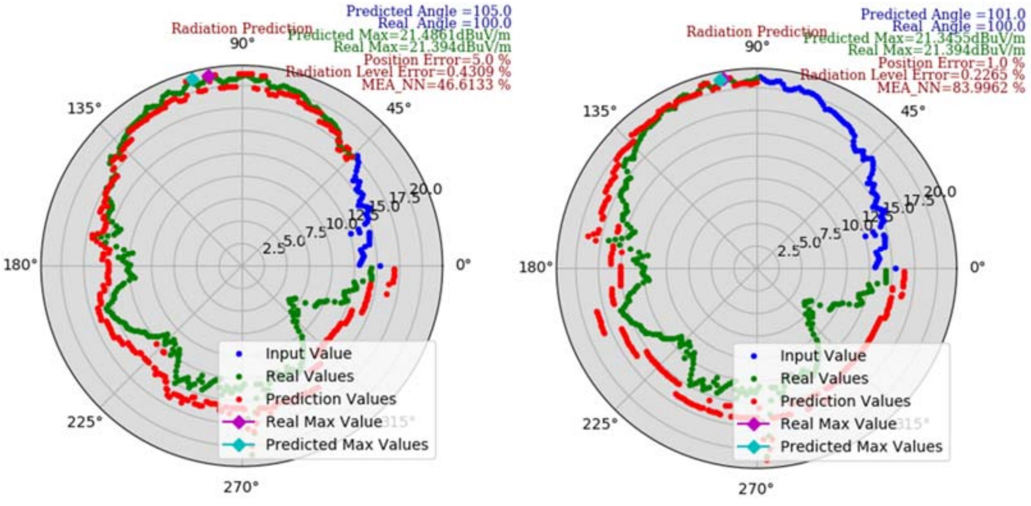
Fig. 9 EMI measurements results for three different EUTs in SAC, Cetecom GmbH, Essen, Germany



(a)

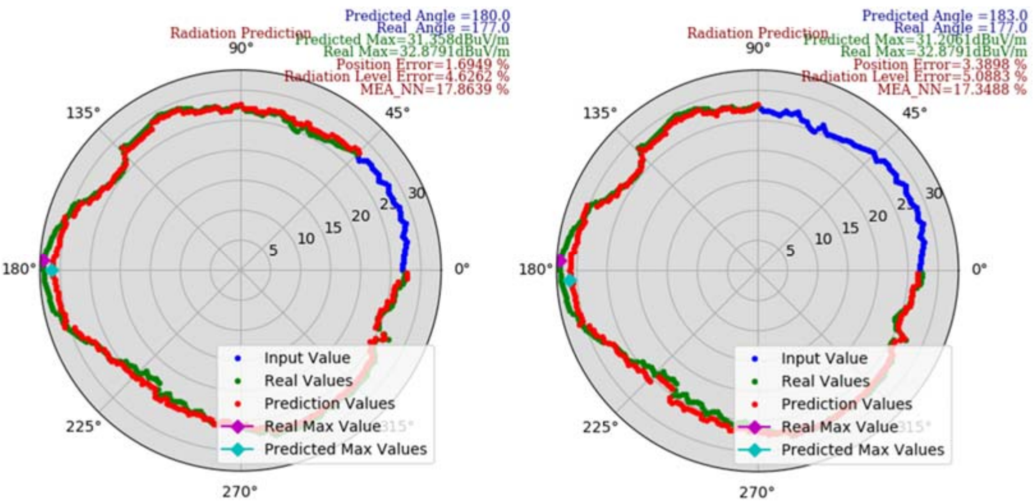
(b)

Fig. 10 Position and radiation level errors of predicted angle and radiation level for critical frequency 124.99 MHz and inputs range, (a) (0°-45°), (b) (0°-135°)



(a) (b)

Fig. 11 Position and radiation level errors of Predicted Angle and radiation level for critical frequency 115.68 MHz and inputs range, (a) (0°_45°), (b) (0°-90°)



(a) (b)

Fig. 12 Position and radiation level errors of Predicted Angle and radiation level for critical frequency 648.01 MHz and inputs range, (a) (0°_45°), (b) (0°-90°)

TABLE III
POSITION, RADIATION LEVEL AND MEAN ABSOLUTE ERRORS FOR THE FIRST CHOSEN CRITICAL FREQUENCY TO DEFINE THE POSITION OF MAX RADIATION (F = 115.68 MHZ, REAL TURNTABLE ANGLE = 100°, REAL RADIATION LEVEL = 21.349 DBUV\M)

Scenario	Predicated Angle (Position of max Radiation) (degree)	Predicated radiation level dBmuV/m	Position Error	Radiation Level Error	MEA
1	105	21.4861	5.0%	0.4309%	46.613%
2	101	21.3455	1.0%	0.2265%	83.996%
3	100	21.349	0%	0%	78.922%
4	100	21.349	0%	0%	21.092%
5	100	21.349	0%	0%	18.649%
6	100	21.349	0%	0%	32.907%
7	100	21.349	0%	0%	18.203%

TABLE IV
POSITION, RADIATION LEVEL FREQUENCY AND MEAN ABSOLUTE ERRORS FOR THE FIRST CHOSEN CRITICAL FREQUENCY TO DEFINE THE POSITION OF MAX RADIATION (F = 648.01 MHZ, REAL TURNTABLE ANGLE = 177°, REAL RADIATION LEVEL = 32.8791 DBUV\M)

Scenario	Predicated Angle (Position of max Radiation) (degree)	Predicated radiation level dBmuV/m	Position Error	Radiation Level Error	MEA
1	180	31.358	1.6949%	4.6262%	17.863%
2	183	31.2061	3.3898%	5.0883%	17.348%
3	176	31.9705	0.565%	2.7634%	34.203%
4	180	33.5625	1.6949%	2.0787%	27:373%
5	177	32.8791	0%	0%	21.581%
6	177	32.8791	0%	0%	5.7773%
7	177	32.8791	0%	0%	1.1283%

By comparing real and predicted radiation levels in Tables

III and IV, it can be seen that the errors by determining that the turntable angle and radiation value are very small. Fig. 13 shows the average position and level errors.

Fig. 13 Average position Error/Saved time of final measurement of seven scenario

Fig. 13 highlights that we can save 87.5% of the required time to carry out the final measurement to find the turntable angle that meets the maximal radiation level.

VI. Conclusion

In this paper, an approach was described to predict the radiation emission during the turntable movement by the final measurement and to determine the maximum radiated emission position using 1D CNN. Real EMI measurements were used to train the CNN. The database was processed and then fit to our neural network using seven different scenarios applied on three EMI measurements and then compared with the results from Rohde & Schwarz EMC32 software. With an average error below 5% for position prediction for the total experiments, the results show that the prediction performance of the proposed measured method could successfully reduce the needed time to determine the worth position of EUT during the final measurement phase. The proposed measurement method can be considered as a prospective cost-effective and time-efficient EMC measuring method that leads to achieving faster real-time operation and EMI measurements in the case of many critical frequencies by using one EMI measurement during the development process of electronic products which will be tested repeatedly to verify acceptable compatibility with other electronic products.

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