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Development of a Conditional Generative Adversarial Network Model for Television Spectrum Radio Environment Mapping

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ABSTRACT To efficiently use the finite wireless communication resource (radio spectrum), a Radio Environment Map (REM) is needed to monitor, analyse and provide rich awareness of spectrum activities in a radio propagating environment. REM shows radio coverage metrics in a geographical region. A REM construction model with few constraints and optimal performance is needed to better support cognitive radio for dynamic spectrum sharing (DSS) and other benefits of REM. This study aims to estimate fine-resolution REM from sparse radio signal strength measurement. In this study, we utilised conditional generative adversarial network (CGAN) to create a television spectrum radio environment map in order to improve cognitive television white space (TVWS) radio performance in real-time propagation environments. Measurement campaign was carried out to acquire a TV-band (470-862MHz) radio frequency and geographical dataset at Covenant University, Ota, Nigeria. A preprocessing procedure which was implemented with Python script was employed to group the dataset using Nigerian Communications Commission TV spectrum channel spacing and to create incomplete spectrograms for 49 channels. Xgboost, SVM, and kriging variogram models were explored to generate ground truth datasets for the CGAN model training, and the best algorithm was employed. A CGAN REM model was developed using U-Net as a generator and PatchGan as a discriminator. The U-Net generator is a 3-channel input, 16-layer architecture while the PatchGan discriminator is a 6-channel input, 7-layer architecture. The model performance was evaluated using mean square error (MSE) and mean absolute error (MAE). 12 different experiments were carried out varying the training parameters of the CGAN architecture to obtain an optimal model. The achieved root mean square error (RMSE) is 0.1145dBm and MAE is 0.0820dBm, which shows the deviation between the ground truth and the generated REM. This low deviation means that the proposed CGAN REM model possesses an improved accuracy in predicting the spectrum activities within the television spectrum which is considered appropriate for DSS technology. This study also revealed that 41 channels within TV-band in Covenant University are totally unoccupied.

INDEX TERMS Conditional Generative Adversarial Network (CGAN), Dynamic Spectrum Sharing (DSS), Radio Environment Map (REM), Received Signal Strength (RSS), Television white spaces (TVWS).

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I. INTRODUCTION

Wireless communication has been the connection backbone of modern technologies such as Machine to Machine, Internet of Things, Smart City and many others as it provides mobility and connectivity where wired communication is impossible [1][2]. The wireless resource responsible for this connectivity is called the spectrum and it is fixed in nature. However, the increasing demand for wireless connectivity among nodes that comes with these recent technologies makes the need for an efficient use of the scarce spectrum crucial [3]. Over the years, spectrum trading together with spectrum liberalization, has been key to optimizing and rationalizing spectrum use, with constraints upon usage as set by the regulator in Nigeria, the regulation is done either by the Nigeria Communications Commission (NCC) or Nigeria Broadcasting Commission (NBC) [4]. The conventional spectrum allocation system, in which certain bands are only licensed to traditional radio users (such as the military, radio and television broadcasters, and mobile carriers) results in inefficient use of spectrum resources [5]. Moreso, the cost of having license to a spectrum band is very expensive. For instance, in 2001, MTN, Econet wireless and MTel paid US$285 million each to get their licenses while Globacom paid US$200 million in 2003 [4]. Fortunately, the transition from analogue to digital television broadcasting in June 17, 2017 (an Economic Commission of West Africa States' deadline to its member states) has resulted in more white spaces within the television spectrum [6], [7].

The European Communications Commission (ECC) defines a white space as "a label indicating a part of the spectrum available for a radio communication application (service, system) at a given time in a given geographical area on a non-interfering/ non-protected basis with regard to other services with a higher priority on national basis" [8], [9]. The spectrum band for television transmission in Nigeria as allocated by the NCC is 470-862MHz [10] and a spectrum occupancy measurement and analysis of this TV band done by [11] in Osun state University main campus, Osogbo, Nigeria revealed that only 17.9% of the spectrum, on the average, is effectively utilized. However, TVWS has exceptional broadcast features over extensive distances and enables transmissions through high rise buildings, trees and mountains, and these features allow the applications of TVWS in Internet of Things, Machine to Machine, Smart city, wireless sensor network, etc [9][12]. Hence, a rich awareness of the spectrum occupancy and vacancy of TV spectrum is instrumental in exploiting the possibilities in TVWS.

Radio Environment Map (REM) can be viewed as a database that keeps comprehensive and current information on the radio spectrum of a geographical location [13]. A basic REM structure consist of REM manager, storage and acquisition also called the REM content, graphic user interface and measurement capable devices. The REM content is made of three layers which are radio environment layer, radio element layer and radio scene layer [14]. Information regarding spectrum occupancy and vacancy are presented in RF-REM (Radio Frequency REM) which is contained in the radio environment layer of the REM content [15]. RF-REM describes spatial signal strength distribution and provides network coverage information [16]. The information contained in the REM can facilitate dynamic spectrum sharing (DSS) to enhance the operation of cognitive radio [17]. In recent literature, the RF-REM is simply referred to as Radio Environment Map (REM). Several techniques have been explored to construct REM and these techniques are majorly divided into three; direct or spatial statistical method, indirect or model based method and hybrid method [18]. Recent applications and success of machine learning in wireless networks and IoT intelligence have stimulated more interests in learning-based radio map estimation as another promising direction [16], [19], [20].

Similar works that employs the learning based approach uses simulations or the model based approach (indirect method) to generate the dataset [16], [21], [22], however, this work entails the development of a CGAN REM model using field measurement (direct method) containing buildings information, propagation model or information about the transmitters whose coverage are present in Covenant University campus, Ota, Nigeria. Also, the developed model has the ability to construct accurate REMs from sparse RSS measurements.

This current study utilises CGAN to construct television spectrum REMs in Covenant University, located in Ota, Nigeria. The objective of this work is to create a REM model for cognitive TVWS radio by utilising field measurements obtained from Covenant University. This addresses the constraints of current approaches by solely utilising the received signal strength (RSS) and geographical locations where the RSS measurements were taken, without relying on building or transmitter information. Furthermore, the dataset utilised in this study consists solely of field measurements and does not include any software-generated simulated data. The CGAN model employed effectively represents the radio propagation phenomena of Covenant University campus during the training process, credit to generalisation capability of CGAN. Hence, the methodology employed can be readily expanded to encompass other campuses. The performance of the model built in this study is assessed using suitable error metrics and compared with the findings of [22]. Specifically, the following are the contributions of this work.

- The model built in this study just requires RSS measurements and their corresponding geographic locations. An advantage of this approach, compared to other advanced methods such as those proposed by [23], [24] and [22], is that it does not require additional information such as transmitter location, distances between transmitters and measurement locations, or cell association.
- In contrast to the aforementioned methodologies, the proposed model does not rely on any path loss model and is solely based on field data and not simulated data.
- This study presents a field measured RSS dataset of Television spectrum (470 – 862MHz) in Covenant University, Ota, Ogun state Nigeria, which can be used for further research.

- The CGAN REM model developed in this work is not only useful for cognitive TVWS radios but for wireless communication interference management, coverage analysis among many others.
- The work also presents the list of TVWS channels available within the university campus.

We organize the remainder of this work as follows:

- an overview of related works regarding radio environment map, generative adversarial network (GAN) and conditional generative adversarial network (CGAN) models;
- description of the radio propagation environment of Covenant University, acquisition of dataset and its preprocessing. Also, a detailed presentation of the proposed REM estimation model based on CGAN;
- presentation of the experimental result; and
- conclusion of the research work.

A. Related Works

Numerous techniques have been proposed in the literature for REM construction using machine learning. For instance, [20] conducted a contrast analysis on SVM, KNN, LightGBM, and XGBoost, focusing on their performance. The results revealed that the tree-based models, namely XGBoost and LightGBM, outperformed the other models. Nevertheless, the methodology is exclusively employed for wireless local area networks and cannot be extrapolated to large-area cellular networks based on the available data. In [25], an approach for predicting path loss (PL) in wireless service area planning is proposed, utilising a two-step artificial neural network method. Given that high path loss region is complex and reduces the accuracy of path loss prediction by the artificial neural network (ANN), an area classification technique was used before predicting the path loss. However, it is necessary to pre-train the network for multiple city maps, since each trained network is peculiar to a certain map. The study conducted in [24] presents a sophisticated deep learning technique that effectively generates radio maps based on the city's layout, transmitter placement, and, if available, pathloss measurements and car positions. The study also devised methods for translating the knowledge gained from a huge collection of roughly simulated radio maps to real-world scenarios. In [26], a feed forward neural network is utilized to enhance the performance of Kriging in the creation of REMs through a measurement-based experiment.

Among the learning-based methods for REM construction, Generative Adverbial Network (GAN) and CGAN have proven to produce more realistic and accurate results due to the robustness of their architectures which comprises of both regression (generator) and classification task (discriminator), and their ability to exhibit superior generalisation capabilities in an examined scenarios, particularly when the input distribution does not align with the training dataset [22]. The work done in [27], through the process of colour mapping, REM estimation task was converted into image reconstruction task using a GAN model called map estimation GANs (MEGANs). The model was developed using an analogy of auto-encoders and deep convolutional structure to design the generator and the discriminator. However, the dataset used for the training and testing of the MEGANs were complete images generated through simulation. The MEGANs model was evaluated using average image reconstruction errors (AIREs) and the results were compared with that of inverse distance weighted (IDW), L-krig and E-krig algorithms. An extension of former work was done in [21] where incomplete REM images were used as the training data which relaxes the requirement for complete REM images. In this case, an improved GAN model was developed named pixel regression framework (PRF) which contained an improved feature extraction ability for the incomplete REMs and a random pixel sampler which samples the output of the generator before they are fed into the discriminator for classification task. The performance of the model was done with and without the feature enhancement module and the AIREs were compared with that of IDW and Kriging. However, the incomplete REMs dataset was also gotten through simulation. In [16], a two-phase learning framework called radio map estimation GAN (RME-GAN) was developed by integrating radio propagation model and designing a conditional generative adversarial network. In the initial phase, exploration of global information to extract the radio propagation patterns were done. In the subsequent stage, the attention shifted to examining local characteristics to estimate the impact of shadowing on radio maps through geometric and frequency downsampling. This was done to train and optimise the CGAN. Thereafter, a comprehensive experimental comparison with kriging, radial basis function interpolation, model based interpolation, traditional CGAN, auto-encoder, deep auto-encoder and Unet in terms of both reconstruction accuracy and fault diagnosis were done and results shows the robustness and performance advantages of the RME-GAN. However, the RadioMapSeer dataset, obtained through simulation (using Winprop software), which captures transmitters and buildings information was used. The work done in [28] presents a novel framework for radio signal generation called Radio GAN using Generative Adversarial Networks (GANs), addressing the challenges of synthesizing raw signal data. The authors analyze the difficulties GANs face in synthesizing radio signals, emphasizing the need to model complex multi-dimensional probability distributions. They highlight issues related to the identically distributed nature of radio samples and the complexity of the underlying sampling distribution. The framework includes an unrolled generator design which is design to allow for better modeling precision by leveraging domain knowledge and estimated pure signal distributions, an energy-constrained optimisation algorithm that enhances training stability and convergence, making the learning process more effective and an experimental setup which involved benchmarking two radio recognition tasks: modulation recognition and RF fingerprinting. The results obtained demonstrate that the proposed GAN framework (Radio GAN) effectively learns transmitter characteristics and various channel effects, leading to accurate modeling of the underlying sampling distribution of radio signals and it also shows that the framework outperforms conventional GANs, achieving higher quality signal data synthesis and satisfactory performance in downstream tasks, such as modulation recognition and RF fingerprinting. For future work, an in-depth analysis of a signal data distribution from a wider perpectives could be done. In [22], a pair of deep-learning models (Unet and CGAN) called DeepREM was developed. DeepREM has the ability to estimate REMs from limited measurements without a need for any supplementary information, although a physical ray-tracing simulator with building and geographic data was utilized during the model training, but not for its operation afterwards. The DeepREM models possess the capacity to accurately predict base station (BS) coverage and reference signal received power (RSRP). The root mean square error (RMSE) and mean absolute error (MAE) attained for estimating reference signal received power (RSRP) are 6.32 and 4.54 decibel milliwatts (dBm), respectively. The error rate for estimating BS coverage was approximately 11%.

II. MATERIALS AND METHODS

The study leverages the Design Science Research (DSR) approach. The research approach is presented in Figure1 utilising a flowchart. Measurement campaign of radio signals operating within the television spectrum (470 – 862MHz) were carried out to obtain their received signal strengths at different sampled locations on the campus. The radio and geographic information (i.e RSS, frequency, longitude, latitude and altitude) recorded are stored in a local database. These acquired data are preprocessed and transformed into images. A CGAN model for Radio Environment Map construction was developed using U-NET as generator and PatchGAN as discriminator. However, SVM, Xgboost and different variogram model of kriging approach were exploited in providing the CGAN model ground truth dataset for training. The estimation accuracy and quality of REM constructed are evaluated using MSE, MAE, RMSE and bull-eye effect.

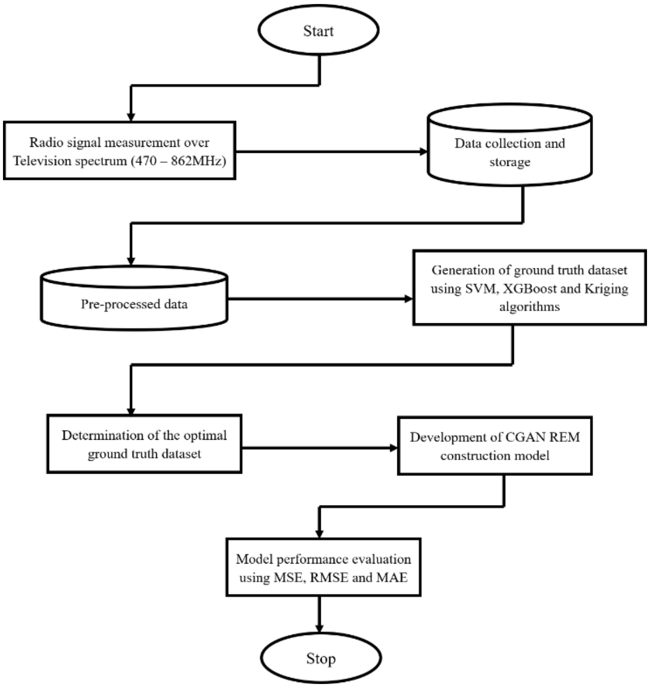

FIGURE 1. Flowchart of research approach

A. Overview of the Campus Propagation Environment

A thorough field measurement campaign was conducted on the Covenant University campus utilising the drive test methodology. The campus is located at kilometre 10 on Idi-Iroko Road in Ota, Canaanland, Ogun State, Nigeria. The geographical coordinates of the location are Latitude 6°40'30.3"N and Longitude 3°09'46.3"E. The Covenant University campus features a modern and advanced infrastructure, which includes advanced lecture halls, tall administrative buildings, four-storey residential buildings, a high-rise research and innovation hub, a top-quality stadium complex, a contemporary health centre facility, well-maintained roadside trees, lively flowers, parks and gardens, street lights, signposts, and billboards etc. Figure 2 exhibits an aerial perspective of the physical environment. The majority of these physical structures possess significant heights that impede direct view yet create indirect signal pathways for wireless communications in radio frequencies.

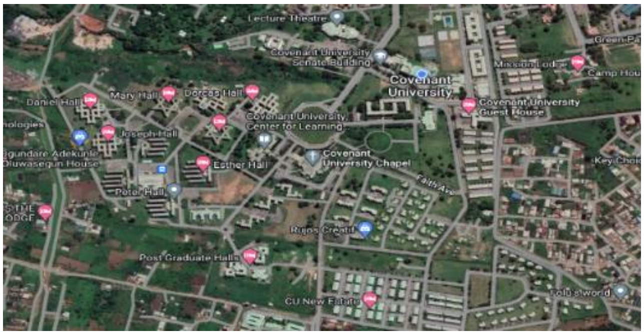

FIGURE 2. Physical environment of Covenant University campus

B. Radio Signal Measurement Campaign

A system for drive test was explicitly setup for the field measurement campaign. The equipment, devices and software that made up the measurement campaign setup include: handheld RF explorer spectrum analyzer, a GPS receiver, a python script that runs on a personal computer (laptop) and a motor vehicle. An ISM COMBO RF Explorer spectrum analyzer (with frequency range 50kHz - 960MHz and 2350 - 2550MHz) was used to receive radio signal information and it was connected through a Universal Serial Bus (USB) port to a Z book HP laptop. During the measurement acquisition phase, a magnet mount USB GPS receiver was utilized to monitor and record geographic information. The laptop also hosted a python program which controls, logs and stores information from the spectrum analyzer and GPS antenna. The information collected are stored in a csv file hosted on the laptop.

Measurements of radio signals were carried out along 14 drive test survey routes and some selected pedestrian pathways within Covenant University campus in order to adequately represent the wireless channel characteristics of a typical smart campus environment. Due to the horizontal accuracy of the GPS antenna, measurements were taken at an interval of 15 - 20m, hence, 105 locations were taken. The sampled locations of the study area where readings were taken is shown in Figure 3. At each location, it took an average of 5 minutes to log and store both the radio and geographical information. Table I provides a first order statistical description of the data acquired during the measurement campaign.

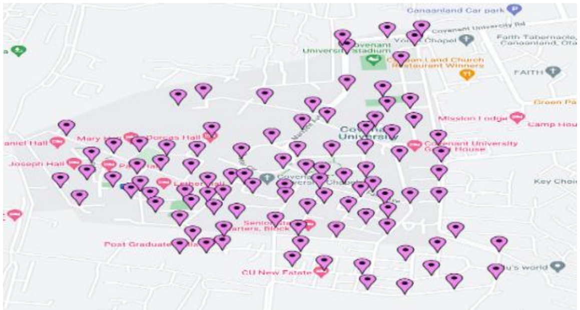

FIGURE 3. Sampled location where measurements were taken

TABLE I
DESCRIPTIVE FIRST-ORDER STATISTICS OF ACQUIRED DATA.

	Frequency (MHz)	Amplitude (dBm)	Latitude (˚)	Longitude (˚)	Altitude (m)
Mean	685.1299	-94.5559	6.66999	3.1591217	57.3852020
Median	685.6065	-97.0	6.66965	3.159493183	57.085
Standard Deviation	124.5787	9.76349	0.00313029	0.0030579	4.814599
Variance	15519.85	95.32578	9.798×10^{-6}	9.351×10^{-6}	23.18036
SED	1.70384	0.133534	4.28125×10^{-5}	4.18235×10^{-5}	0.0658484
Kurtosis	-1.19994	2.963718	-0.13796246	-0.89219859	-0.374945
Skewness	-0.0006518	1.682284	0.40968532	-0.29810230	0.2768737
Range	429.946	57.0	0.01362896	0.01237844	22.69000
Minimum	470.0	-108.0	6.66403355	3.152511425	45.24
Maximum	899.946	-51.0	6.677662508	3.164889867	67.93
Data Points	5346	5346	5346	5346	5346

C. Data Preprocessing

The channel spacing for Television spectrum in Nigeria is 8MHz [29], hence, the data acquired at each location is grouped into 49 channels. Locations where incomplete sweeping took place were deleted from the dataset. Pandas and numpy python libraries were used to achieve the dataset sorting and grouping. Conditional generative adversarial networks (CGAN) is a deep learning model suitable for image enhancement tasks among others. Thus, the radio and geographical data for each channel had to be transformed to the equivalent images. Images are made of several pixels, and each pixel is a grid point. The position and colour of the point relative to the vertical and horizontal axes play a crucial role for identification of pattern. The 2D image signals that could be obtained from radio signals are spectrograms, eye diagrams and constellation images. For the sake of developing CGAN model that is based on the convolution neural network (CNN) architecture, spectrograms are leveraged in this study. Matplotlib python library was used to transform the numerical dataset to images using the power spectral density (spectrogram) approach. Figure 4 shows the transformed data after grouping for channel 7 (518-526MHz).

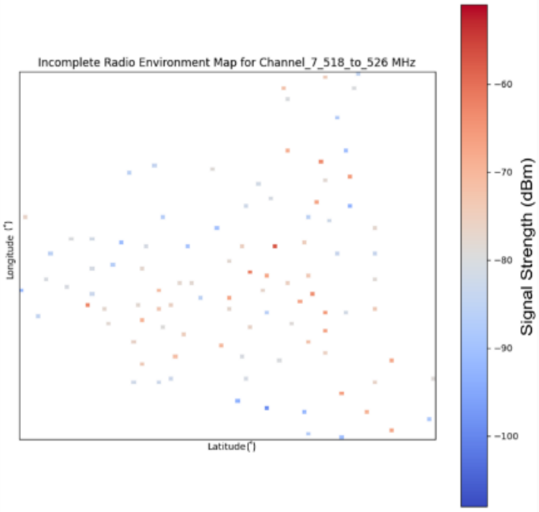

FIGURE 4. Transformed dataset for Channel 7 (Incomplete REM)

D. Generation of Ground Truth Dataset

CGAN model trains two neural networks; a generator and discriminator. The generator takes the incomplete spectrogram as input while the discriminator takes both the output of the generator and ground truth image as inputs during training. Hence, the need for a ground truth dataset. Generating the ground truth dataset is a regression task and the major approaches to do this are; model based and model free method. For this study, consideration that the transmitter locations are out of the coverage area of interest and the transmitters parameters are not available, therefore, the three model free methods are used and their outputs were evaluated using RMSE, MAE, ability to estimate for all channels and the bull-eye effect while the best performing method was used to provide the ground truth dataset for the CGAN training. The three approaches used are Support Vector Machine (SVM), XGBoost and different variograms Kriging. Table II presents the evaluation obtained from the different algorithms used in generating the ground truth dataset and Figure 5 shows channel 1 (470-478MHz) ground truth generated using the spherical variogram model of kriging method.

TABLE II
EVALUATION RESULTS OBTAINED IN GENERATION OF GROUND TRUTH.

Algorithm	MSE (dBm)	MAE (dBm)	Comment
XGBRegressor	36.607	4.4882	Sharp fall among adjacent pixel values (Bull-eye effect).
SVM	39.880	4.680	Presence of bull-eye effect.
Kriging (Gaussian Variogram)	33.79	4.665	Presence of bull-eye effect.
Kriging (Hole-effect Variogram)	33.80	4.669	21 channels estimation were overfitted.
Kriging (Spherical Variogram)	37.62	4.627	Estimated for all channels without overfitting or bull-eye effect.

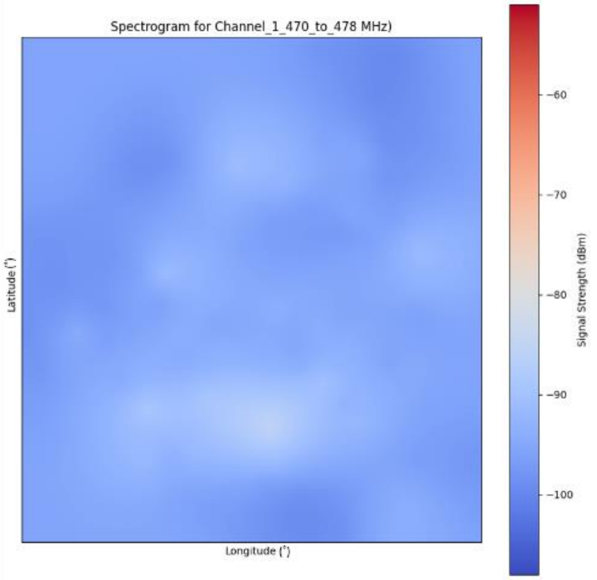

FIGURE 5. Ground Truth generated using Kriging (Spherical variogram model)

E. Development of CGAN REM Construction Model

Conditional generative adversarial networks (CGANs) are an extension of the original generative adversarial networks (GANs), designed to incorporate additional information into the generation process [22]. GANs, introduced by [30] consist of two neural networks: a generator and a discriminator, which engage in a minimax game. The generator aims to produce data indistinguishable from the real data, while the discriminator attempts to distinguish between real and generated data. The adversarial nature of this training process results in the generator learning to produce highly realistic samples [30]. However, GANs in their original form generate data without any control over specific attributes or features. For instance, generating an image of a specific class or type, such as a particular animal or object, is not feasible with vanilla GANs [31]. This limitation prompted the development of Conditional GANs (CGANs), which enable more controlled and targeted data generation [16].

The main distinction between GANs and CGANs is the integration of supplementary information, referred to as conditioning variables, into both the generator and discriminator. This further information enables more accurate manipulation of the produced data [32], [33]. Hence, the components that made the CGANs architecture are;

1) Conditional Generator

In a conditional generative adversarial network (CGANs), the generator receives not only a random noise vector but also a conditioning variable. This variable could be a class label, a textual description, or any other relevant information that specifies the desired characteristics of the generated data. The generator then produces samples conditioned on this input, enabling the generation of specific types of data [34]. The generated sample can be expressed mathematically as shown in equation (1).

$$G(P|u) \qquad (1)$$

where P is the random noise vector and u is the conditional variable.

2) Conditional Discriminator

Similarly, the discriminator in a CGANs is provided with both the data sample and the conditioning variable. The objective is to ascertain the authenticity of the sample by evaluating the provided condition. This configuration guarantees that the discriminator assesses the genuineness of the data within the framework of the conditioning variable [35]. The discriminator function can be expressed mathematically as shown in equation (2)

$$D(Q|u) \qquad (2)$$

where Q is the data sample and u is the conditional variable.

Both the conditional generator (CG) and discriminator (CD) are trained concurrently. The parameter for CG are optimized in order to minimise $\log\left(1 - D\left(G(P|u)\right)\right)$ and that of the CD is also optimised in order to minimize $\log D(Q|u)$, as though they were playing a two-player min-max game with value-function $V(CG, CD)$ as expressed in equation (3) [16]:

$$\min_{cG}\max_{cD}\ V(CD, CG) = \mathbb{E}_{x\sim_{Pdata}(x)}[\log D(\mathrm{Q}|\boldsymbol{u})] + \mathbb{E}_{z\sim_{Pz}(z)}[\log(1 - D(\mathrm{G}(\mathrm{P}|\boldsymbol{u})))] \qquad (3)$$

The need for conditional generative adversarial networks (CGANs) arises due to the constraints of standard generative adversarial networks (GANs) in applications that need precise and controlled data production. There are multiple reasons that drive the development and widespread use of CGANs [36]:

(i) Controlled Data Generation

Generating data with certain traits or characteristics is necessary for many practical applications. For instance, in the context of picture production, there may be a requirement for images that depict particular objects, scenes, or artistic styles. CGANs allow for meticulous manipulation of the produced content by conditioning the production process based on desired qualities.

(ii) Enhanced Applications

CGANs expand the scope of GANs to encompass a wider array of tasks, such as image-to-image translation, super-resolution, and text-to-image synthesis. Generating data with certain attributes is a common requirement for these tasks, which makes CGANs a suitable choice.

(iii) Improved Diversity

By integrating conditioning factors, conditional generative adversarial networks (CGANs) have the ability to produce a wider array of samples that adhere to specific conditions. This results in improved coverage of the data distribution and helps to address issues such as mode collapse, which occurs when the generator only produces a narrow range of samples.

CGANs' capacity to produce conditioned data has resulted in its utilisation across diverse fields such as [36], [37];

- Image Generation: CGANs are extensively employed for the purpose of generating images based on certain labels or qualities. As an illustration, they have the ability to generate photos that belong to particular categories, like dogs, cats, or cars, using provided class names.
- Text-to-Image Synthesis: CGANs have been utilised to produce images based on textual descriptions. By conditioning on textual input, these models have the ability to generate visuals that accurately match the provided descriptions. This capability opens up possibilities for use in content production and virtual reality.
- Image-to-Image Translation: CGANs are commonly used for image-to-image translation tasks, which involve transforming sketches into pictures, grayscale images into colour, or day images into night images. In this scenario, the conditioning variable refers to the source image, while the generated output corresponds to the translated image.

- Super-Resolution: CGANs have the ability to improve the resolution of low-quality images by including the low-resolution input into the generation process. This results in high-resolution outputs that maintain the original content's intricacies and characteristics.

While CGANs have achieved notable advancements, they continue to face specific challenges that prompt additional scrutiny and enhancement, some of which are [38];

- Quality of Generated Data: Assessing the quality of conditioned data poses a considerable challenge. It is essential to create resilient measures for evaluating the accuracy and variability of produced samples within the framework of conditioning factors.
- Training Stability: Similar to conventional generative adversarial networks (GANs), conditional GANs (CGANs) may encounter challenges related to training instability. The pursuit of stable convergence and the prevention of phenomena like mode collapse are current focal points within the realm of research [39].
- Ethical Considerations: The capacity to produce authentic conditioned data gives rise to ethical considerations, especially within the realm of generating falsified or deceptive information. It is imperative to tackle these concerns by means of formulating policies and implementing technological measures [40].

In this work, we adopted a CGAN architecture to develop a REM model that generates a complete REM when fed with sparse measurement of RSS (incomplete REM) of any channel within the identified 49 channels of the TV spectrum in Covenant University. The CGAN model used for pixel regression task (Pix2Pix framework) in this study has a UNet architecture as the generator and PatchGAN as discriminator. From the model architecture as shown in Figure 6, during training, the generator (i.e. the UNET) takes in the incomplete spectrogram per channel and output an estimated complete spectrogram while the discriminator receives both the generator’s output and the ground truth spectrogram as inputs. The classification output of the discriminator i.e., the loss function between the real (ground truth) and the fake (generator’s output) are used to adjust the weights of the generator through back-propagation until the discriminator is fooled (unable to differentiate the real from the fake). Table III and IV outlines the structure of the U-NetGenerator and PatchGan discriminator respectively.

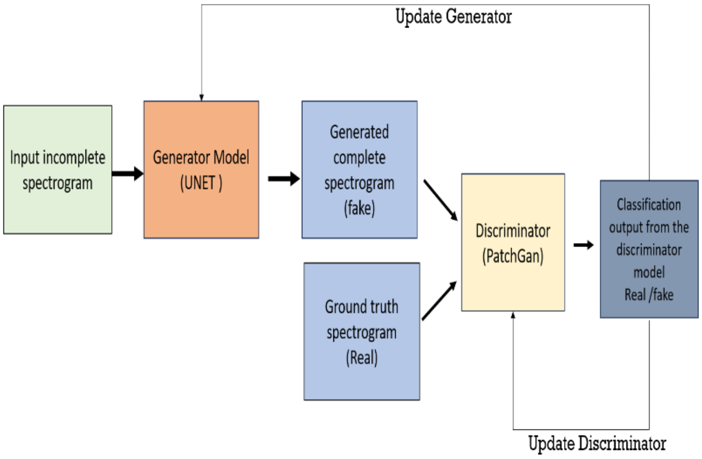

FIGURE 6. **CGAN Model Architecture**

TABLE III
Structure of U-NetGenerator

Layer	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Input Channels	3	64	128	256	512	512	512	512	512	1024	1024	1024	1024	512	256	128
Output Channels	64	128	256	512	512	512	512	512	512	512	512	512	256	128	64	3
Dropout	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.5	0.5	0.5	-	-	-	-	Output layer

NB: All the layers had batch normalization except layer 1 and 16.
For all layers the kernel size is 2, stride padding is 1 and the type is Conv2d.
The activation for layer 1-8 is LeakyReLU (Negative slope: 0.2) while that of layer 9-15 is ReLU.

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TABLE IV
STRUCTURE OF PATCHGAN DISCRIMINATOR

Layer	1	2	3	4	5	6	7
Type	Conv2d	Conv2d	Conv2d	ZeroPad2d	Conv2d	ZeroPad2d	Conv2d
Input Channels	6	64	128	-	256	-	512
Output Channels	64	128	256	-	512	-	1
Stride	2	2	2	-	1	-	1
Padding	1	1	1	-	1	-	1
Dropout	0.2	0.2	0.2	-	0.2	-	-

NB: The activation for all layers is LeakyReLU.

III. RESULT AND DISCUSSION

a) *The CGAN REM Construction Model*

In order to evolve the pre-trained CGAN model in this study, several experiments were performed using the preprocessed training datasets and by varying the epoch number, generator and discriminator learning rates, however, 12 experiments were recorded. Figure 7 shows a sample of the training dataset and Figure 8 shows that of the testing data for channel 42. For the evaluation, the training dataset constitute 80% of the acquired data points per channel while the testing dataset is 20%. The configurations and evaluation for each experiment are presented in Table V.

After an exhaustive number of trials for different learning rates of the generator and discriminator, convergence was observed when the generator learning rate is 2×10^{-4} and that of the discriminator is between 2×10^{-4} and 2×10^{-8}.

Therefore, the parameters of the developed CGAN REM construction model were evolved experimentally varying the learning rates of the discriminator from 2×10^{-4} through 2×10^{-8} and the number of epochs.

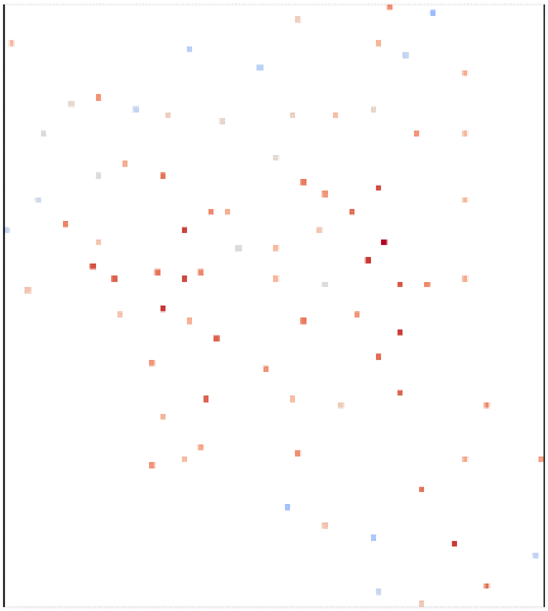


FIGURE 7. Training Dataset for Channel 42 (798 – 806MHz)

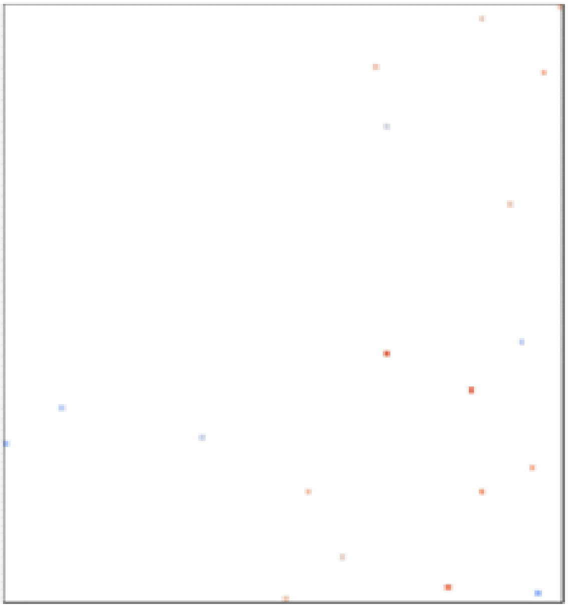


FIGURE 8. Testing Dataset for Channel 42 (798 – 806MHz)

To achieve an optimal model for REM construction several experiments were conducted. A total of 12 experiments were recorded and evaluated using MSE and MAE. The evaluation of result from each experiment was done during training and testing as shown in Table V.

It was observed that Exp. 12 has the lowest MSE value of 0.0005540dBm and also the lowest MAE value of 0.0202425dBm during training while Exp. 11 has the lowest MSE value of 0.0131261dBm and also the lowest MAE of 0.08101313dBm during testing. Exp. 5 (whose generator learning rate is 2×10^{-4}, that of its discriminator is 2×10^{-6} and has epoch number 300) testing result outperformed the training result, which is against the convention, however, when the epoch number was increased to 500 (i.e., Exp. 6) the testing result became lower than the training result. This shows that the epoch number is a vital training parameter in obtaining a stable CGAN model.

Considering the overall performance of the 12 experiments together with one of the objectives of this study (i.e., to generate a complete REM from sparse measurement), Exp.

11 whose generator learning rate is 2 × 10^{-4}, that of its discriminator is 2 × 10^{-8} and has epoch number of 1000 performed best with MSE of 0.0049179dBm and MAE of 0.0509808dBm during training and 0.01312613dBm and 0.08101313dBm during testing. Though, Exp. 12 has a lower MSE of 0.0005540dBm and MAE of 0.0202425dBm during training as compared to the training results of Exp. 11, the testing performance of Exp.11 is however better than that of Exp. 12 and we align with that, since in machine learning tasks testing results captures the generalization ability of the (pre-)trained model. Figure 9 shows the plot of the generator and discriminator losses against epoch number during training for Exp. 11 while Figure 10 shows generated REM for channel 42 during training. At the testing stage, RSS measurements at known locations different from that of the training dataset were taken, preprocessed and fed into the trained REM-CGAN model. The testing produced for channel 42 is shown in Figure 11. During testing, the transformation of the acquired field dataset into incomplete spectrogram is described in Figure 11(a) and Figure 11(b) shows the complete REM obtained when the incomplete spectrogram is fed into the pre-trained model. The obtained RMSE and MAE are 0.4030dBm and 0.3240dBm respectively.

TABLE V
EXPERIMENTAL CONFIGURATION AND RESULTS OF THE CGAN REM MODEL.

	Learning rate			Training		Testing	
Experiment Number	Generator	Discriminator	Epoch	MSE (dBm)	MAE (dBm)	MSE (dBm)	MAE (dBm)
1	2 × 10^{-4}	2 × 10^{-4}	100	0.0234626	0.127769	0.168195	0.34906587
2	2 × 10^{-4}	2 × 10^{-4}	500	0.1153748	0.2960118	0.260845	0.44810674
3	2 × 10^{-4}	2 × 10^{-5}	200	0.1109927	0.2659299	0.230193	0.4306929
4	2 × 10^{-4}	2 × 10^{-5}	500	0.044351	0.1760729	0.191117	0.38119552
5	2 × 10^{-4}	2 × 10^{-6}	300	0.02711325	0.12337095	0.015808	0.09788804
6	2 × 10^{-4}	2 × 10^{-6}	500	0.04066989	0.16406682	0.170729	0.3564888
7	2 × 10^{-4}	2 × 10^{-7}	400	0.01062855	0.08294822	0.1345681	0.3197264
8	2 × 10^{-4}	2 × 10^{-7}	500	0.15832992	0.34944868	0.1802797	0.3796158
9	2 × 10^{-4}	2 × 10^{-8}	500	0.00292423	0.04414726	0.0318831	0.1368439
10	2 × 10^{-4}	2 × 10^{-8}	600	0.00335801	0.04147238	0.0318006	0.12733626
11	2 × 10^{-4}	2 × 10^{-8}	1000	0.0049179	0.0509808	0.0131261	0.08101313
12	2 × 10^{-4}	2 × 10^{-8}	1500	0.0005540	0.0202425	0.0694008	0.21938577

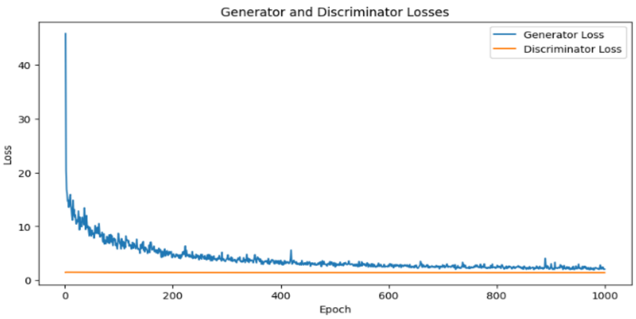


Figure 9. Graph of the Exp. 11 losses versus number of epochs during training

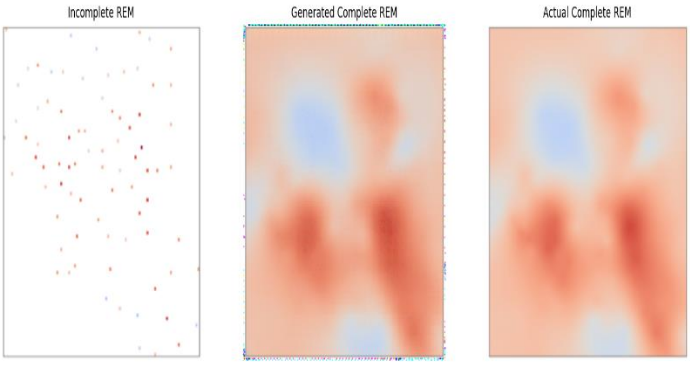
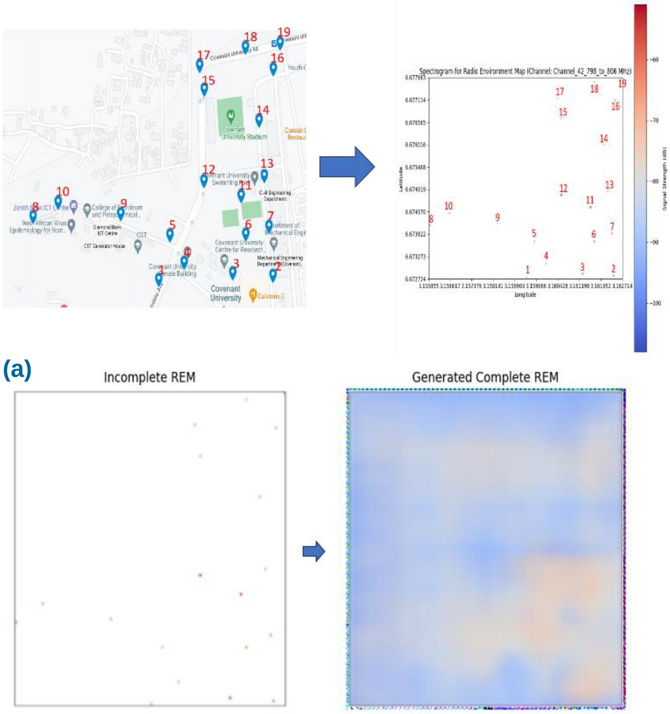


Figure 10. Generated REM for Channel 42 (798 -806MHz) with Training Dataset



(a)

(b)

Figure 11: Testing process for Channel 42 (798 – 806MHz) REM construction

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Figure 12 shows the estimated REM for the 49 television channels within Covenant University. Following the Federal Communication Commission (FCC) standard for declaring a white space in the television band (threshold value of -114dBm) [41], there are eight channels that are occupied, and details of the occupied channels are shown in Table VI.

Comparing this work with the work done by [22], where a DeepREM (which comprises of U-Net and CGAN) was developed using RadioMapSeer dataset to estimate REM from sparse measurement. The DeepREM utilises ray-tracing simulator for its dataset acquisition while this study employs solely field measurement. Also, while the DeepREM uses radio frequency, geographical and building information, this study utilises only radio frequency and horizontal geographical information for its training. The DeepREM achieved RMSE of 6.32dBm and MAE is 4.54dBm while our proposed model RMSE is 0.1145dBm and MAE is 0.0820dBm.

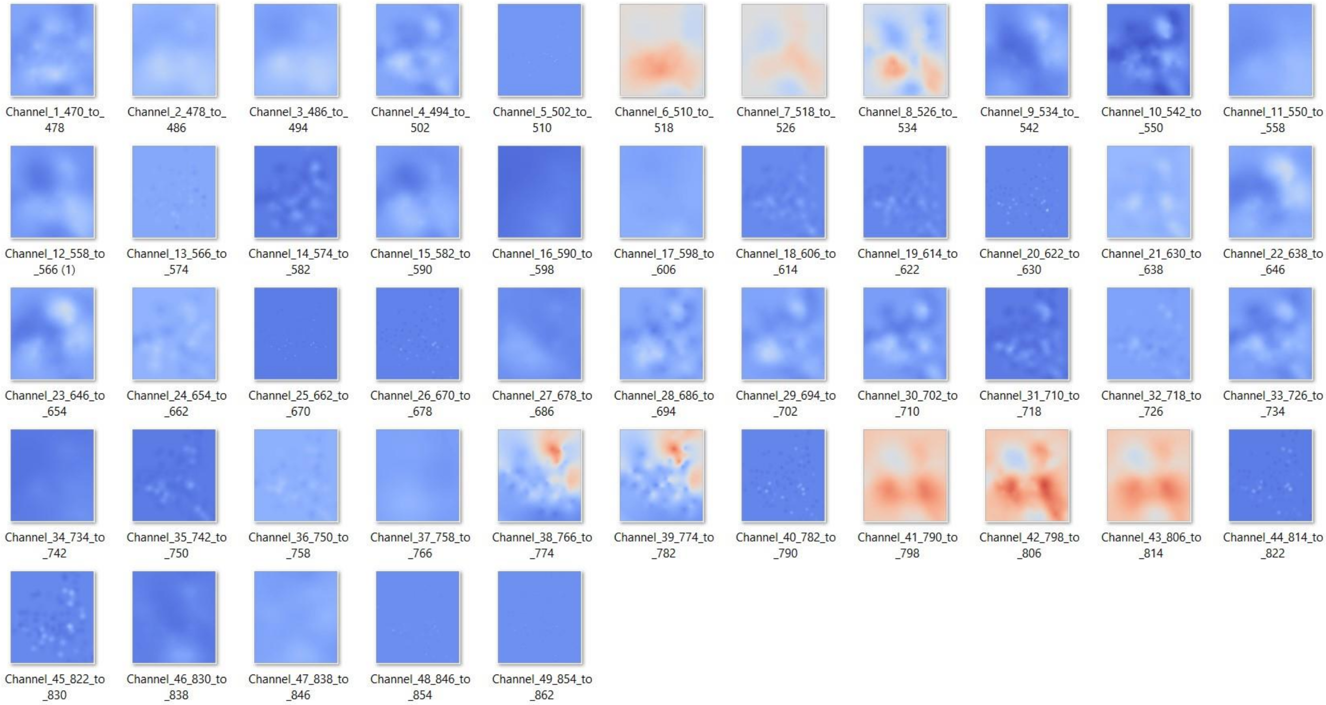

Figure 12: **List of Constructed REM for the 49 Channels**

TABLE VI
LIST OF OCCUPIED CHANNELS

S/N	Channel	Frequency Band (MHz)	Coverage Analysis
1	Channel 6	510 -518	>70%
2	Channel 7	518 – 526	>70%
3	Channel 8	526 – 534	<70%
4	Channel 38	766 – 747	<70%
5	Channel 39	779 – 782	<70%
6	Channel 41	790 – 798	100%
7	Channel 42	798 – 806	100%
8	Channel 43	806 – 814	100%

From this study, it is observed that an optimal REM estimation model is obtainable by using only radio frequency and horizontal geographical information. Also, it affirms that the number of epochs and learning rate are important parameters while training a CGAN REM model. From the coverage analysis, this study reveals that 41 channels within the television spectrum (470 – 862MHz) in Covenant University are fully unoccupied.

IV. Conclusion

This study presented the development of a CGAN REM construction model for cognitive TWVS radios and other wireless communication applications such as coverage analysis, interference management, network planning among others. Unlike recent methods in the literature, the developed model relaxes the need for many information like elevation, cell association, pathloss model, building information during training. Also, the model is trained with field measurement of RSS and their corresponding geographical information from Covenant University, Nigeria and not simulated dataset. To achieve an optimal model for REM construction several experiments were conducted, however, a total of 12 were recorded and the model whose parameters outputs the best performance after evaluation was selected. Extensive testing shows that 8 channels out of the 49 TV channels are occupied while 3 of them have total coverage within the university campus (i.e Channel 41, 42 and 43). The developed model outperforms state-of-art methods in terms of RMSE and MAE. The model attained RMSE of 0.1145dBm and MAE of 0.0820dBm during evaluation. One promising future direction is the use of crowdsourcing approach for data acquisition and development of a database for storage which will enable the model to perform better in dynamic radio environment.

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