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An overview of propagation models based on deep learning techniques

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Abstract— **In this paper, a literature overview of propagation models based on the application of deep learning is presented. Given the shortcomings of traditional empirical and deterministic models, papers dealing with the formation of propagation models are increasingly turning to modern solutions such as deep learning. This paper discusses the classification of propagation models based on deep learning techniques based on their ability to make predictions independently or in combination with a traditional model. Different architectures of deep learning models that are most commonly used in the creation of propagation models are analyzed, such as deep feedforward neural networks, convolutional neural networks and generative adversarial networks. The basic differences arising from different deep learning models and types of input data are analyzed, as well as their impact on the need for expert knowledge in the selection of data that appear as elements in the vector representing input.**

Keywords - deep learning, propagation models, radio propagation

I. INTRODUCTION

The need for the propagation models is as old as the first radio communication systems. Without them, modern planning and efficient management of wireless communication systems is not possible [1]. Therefore, creating a model that can perform the most accurate prediction, while maintaining numerical efficiency, is a challenge for decades among experts dealing with the propagation of radio signals. The importance of propagation models is mostly reflected in the prediction of propagation loss, which is one of the basic characteristics of radio channels, coverage analysis, determining the received signal strength, link budget, signal-to-noise ratio, … [2], [3]. Accurate estimation of propagation loss forms the basis for good base station site selection and appropriate frequency planning, which is the first step in the development of a radio system [2]. In the literature, propagation models are mainly classified into deterministic and empirical models. Empirical models are based on extensive measurements performed in different environments and different frequency bands [4]. Their advantage is that they implicitly take into account the influence of the environment on signal propagation. Usually, the disadvantage is insufficient efficiency, which depends on the accuracy of the measurements based on which the model was built, but also on the similarities between the analyzed environment and the environment in which the measurement was performed [5]. Moreover, the lack of empirical models accuracy is influenced by the fact that they use a very limited number of parameters to describe the environment [6]. On the other side, deterministic models are based on the laws of physics and are generally characterized by greater precision than empirical models. Unlike empirical models, they require more detailed information about the environment [6]. Their disadvantage is reflected in their poor numerical efficiency and the fact that they require an extensive environmental database, which sometimes cannot be provided. They are mainly used for predictions in microcells and indoor environments [5]. Given the shortcomings of traditional empirical and deterministic models, numerous solutions based on the application of modern machine learning and artificial intelligence techniques have been proposed in the literature. The reason for the popularity of applying the aforementioned techniques in building propagation models is their ability to efficiently approximate an arbitrary function that cannot be explicitly described by a formula and depends on several input parameters, which corresponds to the problem of predicting propagation loss. There is a relatively large number of solutions for building propagation models based on artificial intelligence techniques. In this paper, we present an overview of propagation models based on deep learning, a special form of machine learning [7]. To the best of the author's knowledge, such models are mostly based on supervised learning and regression, except when the goal is to classify the obtained value into one of the categories indicating the level of the received signal, as shown in [8].

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II. APPLICATION OF ARTIFICIAL INTELLIGENCE IN PROPAGATION MODELS

Most of the propagation models presented in this paper are based on deep feedforward networks and convolutional neural networks or some of their combined architectures. Deep feedforward networks are also known as feedforward neural networks (FNN) or multilayer perceptron (MLP) and represent one of the deep learning models [7]. The architecture of a single feedforward neural network consists of an input, an output, and several hidden layers. Hidden layers can be considered as a set of units that operate in parallel and represent a function that performs vector-to-scalar mapping [7]. Each unit can be viewed as a neuron that receives information from multiple neurons in the previous layer and computes its output based on this information [7]. The value of the obtained output depends largely on the choice of the activation function, which is necessary for approximation of complex nonlinear functions. Without its application, the output signal would be just a simple linear function [9]. The neuron's activation function maps any input value to the corresponding output from the defined domain. Examples of activation functions are *tanh, sigmoid, softsign, softplus, softmax, ReLU* (Rectified Linear Unit) [9]. The application of ReLU activation function is very common due to its advantage reflected in its simplicity and the fact that its choice eliminates the vanishing gradient problem [10], Fig. 1.

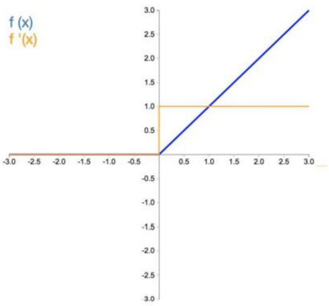

Figure 1. ReLU activation function [9]

The number of hidden layers in the architecture of an MLP network indicates its depth, and the number of units in the hidden layers indicates its width [7]. When the number of hidden layers is small, we speak of shallow neural networks. Each of these architectures has advantages for a particular type of problem [11]. When it comes to building propagation models, most models use an architecture with several hidden layers, i.e., deep feedforward networks. Feedforward in the name means that such networks have no feedback in the architecture, but the information flows in one direction, Fig.2.

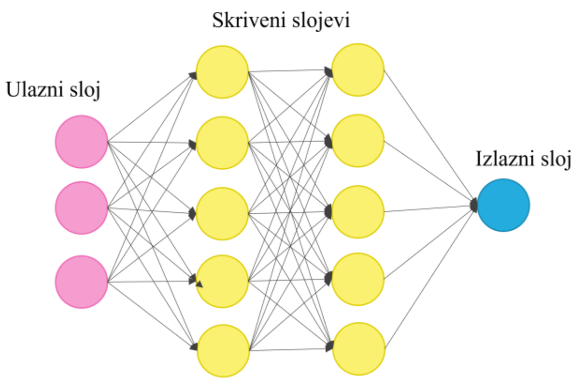

Figure 2. Example of *feedforward* neural network

If there is feedback, then we are talking about recurrent neural networks, which are not considered in this review. In propagation models based on MLP networks, the inputs are vectors of data that arise as a result of the selection of experts that form the model, on which the performance of such models largely depends. Therefore, it is important to make the right choice, taking into account the dimensionality of the input vector and the possible correlation between input vector elements, which are known as features.

Unlike feedforward networks, convolutional networks are a special type of neural networks for data that have a grid-like topology [7]. Most often, and this is the main topic of this paper, this data is in the form of an image, i.e., a matrix with pixels. The architecture of any convolutional neural network consists of several layers that have different functions, such as convolutional layers, pooling layers, and fully connected layers, Fig. 3.

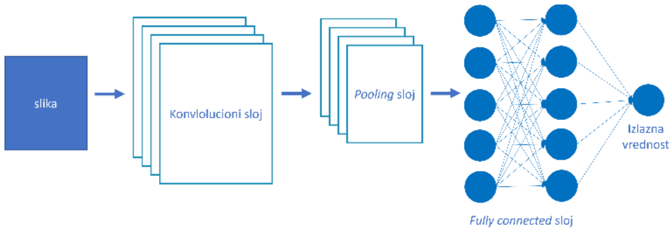

Figure 3. Example of convolutional neural network

A key difference between such networks and the previously mentioned feedforward networks is, among other things, the ability to independently determine from the image the features that are important for solving the task at hand through various layers. These tasks are mostly in the domain of image classification, although there are also examples where convolutional neural networks are used for image-driven regression [12], such as in the creation of propagation models that aim to make the most accurate prediction possible based on images containing propagation-related information.

Some authors in their work compare the performance of a propagation model based on artificial neural network with the performance of a traditional model. The authors in [13] presented the improvement in root mean square error (RMSE) obtained with their solution compared to ITU 452 [14] and the Cost-Hata model [15], which is about 7 dB and 9 dB, respectively, while compared to the ray-tracing modeling approach, the prediction time was reduced even 12 times. Better performance was also observed in comparison with the CI PL [4] and A-B PL [4] models presented in [4]. A comparison with the ray-tracing and urban macro (UMa) 38.901 [16] models at 811 MHz and 2630 MHz is presented in [17]. Here, the improvement of the presented model based on deep learning is up to 4.7 dB compared to the previously mentioned traditional models. In [5], several solutions for propagation loss prediction based on deep learning networks are presented, and the best results show an improvement over the traditional COST-Walfisch-Ikegami (CWI) [18] model of about 3 dB.

III. ARTIFICIAL NEURAL NETWORKS BASED PROPAGATION MODELS

As mentioned in the previous chapter, most propagation models can be classified by the choice of applied neural network type and input data into models such as those based on:

- MLP networks [2] - [4], [13], [19], [20], where the input is a vector of features, selected by the experts building the model,
- models that use images as input data, as is the case with convolutional networks [6], [12], [21] - [25], [26], or
- models that use raw measurement data, as is the case with GAN (Generative Adversarial Networks) networks [27], [28].

A. Propagation models based on feedforward neural networks

A variety of propagation models based on MLP neural networks have been proposed in the literature, taking into account different influences on propagation through the choice of features. Given the importance of the environment for signal propagation, it is very important to consider its influence when building a propagation model. When describing the propagation environment in an urban setting, the influence of buildings and roads on the propagation can be very large. Thus, in [2], the number and percentage of buildings in the signal direction were considered, as well as information about the main and cross roads. The information can also refer to the influence of buildings by considering the number of buildings that the signal passes through on the direct path between the transmitter and the receiver in each of the clusters, where the different clusters can be different types of buildings [13]. In [20], the influence of buildings is analyzed by dividing the path between the transmitter and receiver into an arbitrary number of intervals, within each of which the building with the highest height above the direct optical line of sight is determined and described by parameters such as height above the direct optical line of sight, distance from the transmitter, and width. The authors in [19] consider the influence of buildings and roads by dividing the area of interest into a network of N × N cells, with the center of each cell located on the building or road, depending on the distribution of buildings and roads, where buildings are described by width, height, and length, and roads are described by width.

When describing the influence of the propagation environment, in the absence of information about its geometry and materials, the types of the environment (green areas, forests, tall buildings, sea, wet land ...) can be used as information [4]. It has been shown that the consideration of environmental information in the construction of a propagation model contributes to the accuracy of the prediction [4], [8]. Considering the mentioned information, in the works [4], [8] the replacement of complex 3D modeling was achieved by forming a vector whose dimensions correspond to the number of considered environmental types. Each element of the vector corresponds to the length of the line in the LoS (Line of Sight) direction passing through the corresponding type of environment. The elements of the vector describing the environment can be the number of occurrences of each type of environment within rectangular area with the transmitter and receiver located diagonally in its vertices [4]. There are examples where terrain use and vegetation density are taken into account [29].

Important information also includes the system parameters in terms of frequency, information about the antennas, the positions of the transmitter and receiver, which can be represented by both latitude and longitude [30], the distance between the transmitter and receiver, and information about whether the conditions for direct optical visibility are met [13]. As mentioned earlier, the formation of the input vector can be very challenging. Features must be considered that best describe the influence of the propagation environment and system parameters on the prediction and provide good generalization properties. Consideration must be given to the dimensions of the vector and the correlation that may exist between features. To reduce the dimensions of the input vector while retaining important information, the principal component analysis (PCA) technique is used. By reducing the dimensions of PCA, it also helps to increase the speed of network training and improve the generalization properties of the model [3]. It has been applied in the works [4], [8] to reduce the linear correlation between different types of environments. The analysis in [20] showed that better results are obtained when PCA is applied to the input vector.

B. Propagation models based on convolutional neural networks

Propagation models based on the application of convolutional neural networks require the use of images as input data. The outputs of such prediction models may be scalar values representing the propagation loss (or other relevant parameter) at a location of interest. The outputs may also be images representing a map of propagation loss values (or other relevant parameter) for the area of interest. This corresponds to image-to-image regression characterized by the use of UNet networks [31]. The application of UNet networks for the creation of propagation models is presented in the works [6], [26]. In the work [26], several solutions for the formation of a propagation model based on the application of UNet networks were proposed. One of the solutions contains as inputs morphological images of city and car maps on the road and a morphological image of the transmitter position, while the output are images with corresponding propagation loss values, where each pixel represents a propagation loss corresponding to the location represented by that pixel. In the same work, the application of transfer learning [32] was also considered in the construction of the model. The idea is that based on coarse simulations, the model learns the "bigger picture" and then based on a smaller data set representing simulations with higher accuracy, the model is better adapted to the real field scenario.

In propagation models based on convolutional neural networks, the inputs to the network are usually images that contain important information about the environment, such as aerial photographs [22], [23], which contain information about buildings, roads, and vegetation. Aerial photographs as such provide important information to study the effects of the environment on signal propagation. Therefore, in [22], a grayscale image representing an aerial photograph is used, with the center at the position of the transmitter or receiver, with dimensions 256 × 256, where the value of each pixel corresponds to a 1 m × 1 m area. The application of aerial images is also found in [33], where semantic segmentation is used to divide aerial image into three classes (urban, suburban, and rural). This allows the prediction of propagation losses specific to each type of environment through which the link passes. This can be particularly important when dealing with larger geographic areas where different regions through which the link passes require different propagation models [33]. In addition to aerial photographs, images with information about buildings are very often considered, which is typical for predictions in urban environments. In [22], an image with building information was created, where the parts representing buildings and roads are clearly separated. It has been shown that using such images together with images containing information about the height of buildings gives a lower error in prediction than using just solely aerial image as input. Given the limited availability of aerial images containing information about buildings within an urban area, [23] improves the model presented in [22] for the case where only aerial image is available. The presented solution involves creating images of interest with information about buildings based on aerial image using UNet networks, which are later used as input to the model. Consideration of the influence of buildings in [12] implies as input to the convolutional network an image with the heights of buildings, which is a rectangular area with the transmitter and receiver located diagonally in its vertices. Depending on the distance between the transmitter and receiver, the dimensions of the generated image with the heights of buildings in the area of interest also differ. Each image is reduced to predefined square dimensions before being brought to the input of the convolutional network. By changing the dimensions of the image, the distance information contained in the image is not lost [12].

Most models based on convolutional neural networks consider non-image data as input in addition to images, indicating information such as distance, system parameters, and others. Such additional information can be considered as additional inputs in the form of scalars or vectors [17], [21], [22], [23] or represented by an image [6], [26]. That is, the pixel values of the image used as input to the model can represent any information, so they can indicate the heights of the terrain profile [24], [25], clusters, tilt antennas, antenna gain, frequency [6]. For example, in [26], the transmitter location is represented as a morphological image where the pixel at the location corresponding to the transmitter position has a value of one, while the remaining pixels have a value of zero. In one of the solutions for creating a propagation model in [26], in addition to the morphological images of the city map and vehicle layout and the transmitter location, a grayscale image is input to the network. That image represents a partially filled map of propagation loss values for that area. Non-zero pixel values represent propagation loss at the corresponding location, while values from locations where no measurements were taken are set to zero. This means that the network learns the estimate based on the nominal inputs and the interpolation based on an additional input, which is a partially filled map of propagation loss values. This can be useful in situations where the nominally given inputs do not represent reality accurately enough [26].

An investigation of the influence of image dimensions on the accuracy of the propagation model based on the application of convolutional neural networks is presented in [12], [22]. The analysis in [22] showed a 93% reduction in complexity when the image dimensions were reduced from 256 × 256 to 64 × 64, with an RMSE distortion of 1 dB. Also, in [12], the effect of image dimensions on the achieved performance was studied by comparing the achieved MAE (Mean Absolute Error) for the case where the selected image dimensions of 64 × 64 pixels are compared with image dimensions of 16 × 16, 32 × 32, 128 × 128, and 256 × 256 pixels. It was found that decreasing the image dimensions resulted in worse estimation, while significantly increasing the image dimensions did not have much effect on the improvement.

C. Propagation models based on GAN neural networks

Using GAN networks to build propagation models requires the use of raw data. In addition to convolutional neural networks, GAN networks also allow the creation of models that do not require expert knowledge to determine features, as was the case with models based on the MLP architecture. In [27], the concept of a GAN network that trains raw measurement data for a given scenario is used. It consists of two neural networks, one of which is a channel data generator and the other a channel data discriminator, Fig. 4.

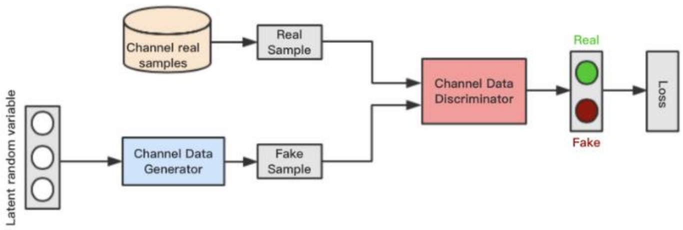

Figure 4. The GAN based wireless channel modeling framework [27]

The generator attempts to produce samples that are as realistic as possible, such as those obtained from measurement campaigns, and thus directly learns the characteristics of the target radio channel. The discriminator is another neural network trained with the goal of more efficiently distinguishing real samples from fake samples, i.e., those generated by generators. Competing these two networks, a channel model is created. Training stops when the discriminator is no longer able to distinguish fake samples from real ones, and then the generator becomes the channel model. The disadvantage of this model is the need for sophisticated and extensive measurements and possible problems with convergence. The generator can find one type of sample with which to fool the discriminator and only make variations of that selection without learning to generate other samples. Moreover, this model is specific to the environment in which the measurement campaign was conducted [27].

An example of using GAN networks for prediction purposes is presented in [28], where the GAN network is trained to produce high-resolution received signal strength (RSS) maps based on RSS maps produced by low-cost/low-accuracy raytracing simulations. In addition, generalization has been achieved to allow the model to be adapted to new frequencies and receiving points. Based on the lower resolution RSS map, the generator creates a higher resolution RSS map that is fed to the input of the discriminator along with the original higher resolution RSS map. The discriminator's task is to detect whether the RSS map is generated or real. With competition between the generator to create the most realistic RSS maps as possible and the discriminator to distinguish real RSS maps from generated ones, both networks learn over time. The generator is a network with a UNet architecture that, in addition to the lower-resolution RSS map, takes as input the frequency, the distance of each receiving point from the transmitter, and the number of obstacles between the transmitter and each receiving point. The discriminator is a convolutional neural network that provides a value between zero and one based on the generated RSS map, indicating how real the generated map is [28].

IV. PROPAGATION MODELS BASED ON A COMBINATION OF TRADITIONAL MODELS AND APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS

In contrast to the models of radio channels presented so far, which are based entirely on neural networks, there are also those that are combined with some traditional models. Such propagation models not only use artificial neural networks to determine the connection between the input data and the desired output, but also use the assistance of traditional propagation models in the prediction. The task of the artificial neural networks in such models is mainly to learn the correction that exists between the prediction results of the traditional model and the measured values, which is why they are also called error correction models [5].

The paper [5] presents a solution for a stand-alone and combined propagation model. In the later one, the neural network is trained to learn the error that exists between the values obtained by prediction using the Cost-Walfisch-Ikegami (CWI) model and the measured results. The error obtained in the prediction process is added to the value obtained by applying the CWI model in order to obtain the final result, Fig. 5. and Fig.6. The comparison of the statistical parameters obtained in the case of the CWI model, the presented error correction model and the stand-alone ANN model shows that the best values of the statistical parameters are obtained by applying the error correction model.

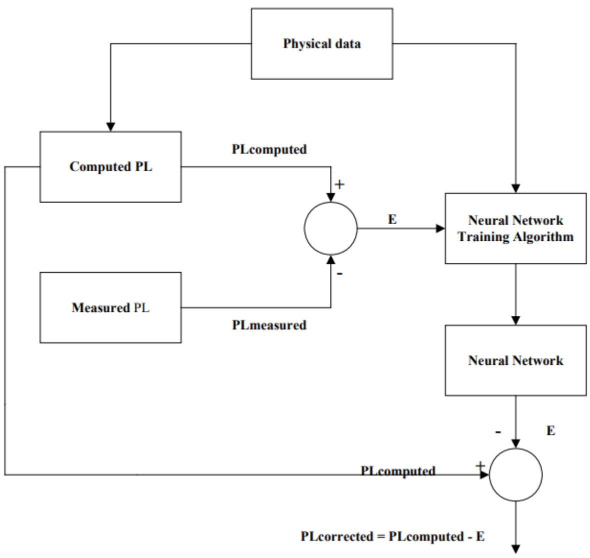

Figure 5. Schematic representation of the error-correction model training process [5]

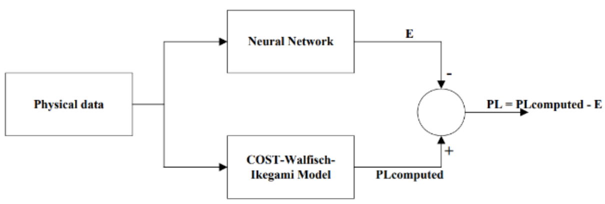

Figure 6. Schematic representation of the propagation loss prediction for the error-correction model [5]

An example of another combined propagation model is presented in [17]. The presented model uses the output of the so-called Uma_B model [16]. The output of the Uma_B model is also fed into the output of the network, Fig. 7. In this way, it is achieved that the model learns the correction added to the value obtained by applying the traditional model. The architecture of the aforementioned model consists of two neural and one convolutional network used for satellite image processing. The outputs of one neural network and the convolutional network are fed into the input of another neural network, which is directly connected to the output, Fig. 8.

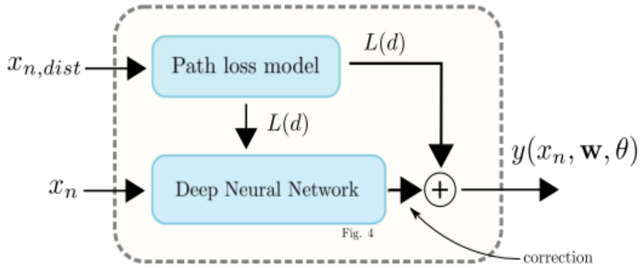

Figure 7. Scheme of operation of the combined model presented in [17]

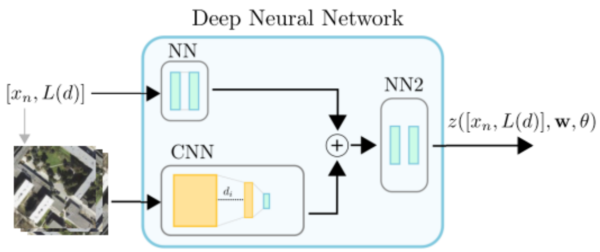

Figure 8. Neural network architecture for the propagation model presented in [17]

A similar model architecture is presented in [21], which is an extension of the work [17], with differences in input parameters and model complexity. The model presented in [21] is combined with the 3GPP UMa [34] model and uses OSM (Open Street Map) images. The created model shows similar performance to [17] with a significant reduction in model complexity.

V. CONCLUSION

In this paper, an overview of some propagation models presented in the literature based on the application of deep neural networks is given. Solutions based entirely on a deep learning architecture are presented, as well as those that combine the application of a traditional model with a deep learning solution. The different model architectures are analyzed with particular attention to the input data used to build the model. The first such propagation models were based on MLP networks, which depend on the selection of features used for prediction and turned out to be a selection of experts that form the model. The most recent work is based on the application of convolutional neural networks, where the model is fed with important information about the environment, system parameters, etc., through the input data given in the form of an image. Table I gives an overview of the models presented in the literature based on the criteria considered in their analysis in this work. When analyzing the quality of the created model by considering the statistical parameters, it is important to pay attention to the range of values (propagation loss, power level, etc.) considered in the calculation of the statistical parameters. Therefore, Table I also contains information about the range of values used in the model evaluation. In the papers where a more detailed analysis is presented, where several solutions are presented based on different architectures, data, etc., Table I shows the results that the authors of this paper consider the most relevant, obtained for an arbitrarily chosen statistical parameter, if there are more. The application of deep neural networks aims not only to reduce the complexity of the models compared to deterministic models and to increase the efficiency compared to empirical models, but also to speed up the prediction process, which can be achieved by using graphics processors. Most recent work aims to create high-performance models that rely as little as possible on expert knowledge, thus reducing prediction errors that may be due to human influence.

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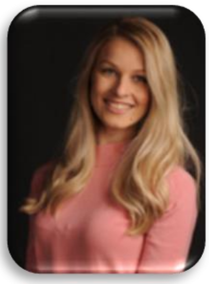

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TABLE I. COMPARATIVE PRESENTATION OF REVIEWED PAPERS

Reference	Neural network type	Input data	Stand-alone/ combined	Operating frequency [MHz]	Approximate signal dynamics [dB]	Evaluation metrics	Evaluation metrics value
[2]	MLP	Engineered features – information about buildings, streets, and environment	Stand-alone	900	80	RMSE	4.85 dB
[4]	MLP	Engineered features – environmental features, information about antenna, base station and receiver location, distance between base station and receiver, frequency, transmit power	Stand-alone	2500	80	MAE	< 3.64 dB
[5]	MLP	Engineered features – information about streets, buildings, distance between transmitter and receiver	Combined	1890		RMSE	6.07
[6]	UNet	Images with clutter, terrain, building, azimuth, tilt, antenna height, antenna gain and frequency information	Stand-alone	/	80	RMSE	7.48
[12]	CNN	Images of the area contained between transmitter and receiver with building height information	Stand-alone	900	90	RMSE	4.42 dB
[13]	MLP	Engineered features – system features (information about antenna, transmitter etc.), environment features (information about LOS/NLOS state, propagation distance, clutter type, etc.)	Stand-alone	2100	/	RMSE	6.19 dB
[17]	CNN for satellite images + FNN for managing engineered features	Satellite images and engineered features (information about position and distance)	Combined	811, 2630	40	RMSE	≈ 4.5 dB
[19]	MLP	Engineered features – geometry of environment and coordinates of receiver	Stand-alone	/	60	MEAN	4.89 dB
[20]	MLP	Engineered features – information on significant buildings and distances along the signal path	Stand-alone	947	80	MSE	51.15 dB^2
[21]	CNN for OSM images + FNN for managing engineered features	OSM (OpenStreetMap) images and engineered features (information about distance, velocity, and frequency)	Combined	811, 2630	60	RMSE	6.3 dB
[22]	CNN	Image data of building occupancy rate and building height data, system parameters including base station specifications and distance between transmitter and receiver	Stand-alone	2000	70	RMSE	≈ 4 dB
[23]	CNN for images + FNN for managing engineered features	Estimated building occupancy images and system parameters (antenna and base station information and distance information)	Stand-alone	2100	60	RMSE	7.54 dB
[24]	CNN	Terrain profile and distance between transmitter and receiver	Stand-alone	1800	80	RMSE	4.9 dB
[25]	CNN	Image with terrain profile	Stand-alone	900	140	RMSE	6.65 dB
[28]	GAN	Low resolution RSS (received signal strength) maps	Stand-alone	$5250 \leq f \leq 5350$	20	MAE	2.8 dB