2020 12th International Conference on Information Technology and Electrical Engineering (ICITEE), Yogyakarta, Indonesia

Propagation Path loss model based on Environmental Variables

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***Abstract*—We have developed a path-loss model that includes environmental variables. We take a sizeable 2-dimensional satellite image of 4 cities, namely Hyderabad, Mumbai, Chennai, New Delhi, and then divide the large 2d image into many smaller images. Then we perform image segmentation using the Maximum likelihood algorithm on each smaller image. Segmentation separates the image into separate areas comprising of pixels with identical qualities. After that, we develop three different 11 input path loss models based on Fuzzy logic, Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS), respectively. Input Parameters to all these three path loss models were %building, %road, %plain, %water, %trees, transmitter terrain height, receiver terrain height, the distance between receiver and transmitter, average clutter height, transmitter frequency, and transmitter height. The output of all the above three models is a path loss. We acquired receiver power levels data in a driving test through different routes in all four cities. We compared measured path-loss values for each route with the predicted values obtained with ANN(with image segmentation), ANFIS(with image segmentation), FCM(with image segmentation), ANFIS(without image segmentation), and empirical path loss models. We measured each path-loss model's accuracy with RMSE (root mean square error) obtained between the predicted & measured path loss values. This paper found that ANFIS(with image segmentation) path-loss model has an RMSE of 2.16 dB, the lowest RMSE among all the considered path-loss models.**

***Index Terms*—ANN, ANFIS, Cognitive Radio, Fuzzy logic, Image Segmentation, path loss.**

I. Introduction

Enabling of secondary access to TV White Space(TVWS) by Cognitive Radio(CR) is an excessively researched technology [1]. We define TVWS as vast portions of the spectrum, which are available based on geography in VHF/UHF bands [1]. CR can use these white spaces. We require good knowledge of the propagation channel for choosing the proper transmission method in a CR, which reduces interference from and to other radios. Path loss is one of the significant propagation channel parameters. VHF/UHF bands affect the propagation of wireless signals in several ways.

We consider the path-loss as the local spatial average measured in decibels. For an urban area, many propagation models are available to estimate path-loss. Many authors empirically derive current path loss models with the linear log-distance model's assumption and compute model parameters with linear regression of collected data. Such models are not appropriate for every area. Generalization of an environment is possible using machine learning methods because these methods learn with training data collected from that environment. The accuracy of models derived from machine learning methods is more than empirical models. The computational efficiency of models derived from machine learning methods is more than deterministic models [2]. Motivated by this, we develop a model using a machine learning method for multidimensional regression of the path loss related to distance, frequency, transmitter height, and many other environmental parameters in the urban environment. Authors [3] propose an image segmentation and 2d aerial images classification for a cellular planning tool. The authors divided the classified image into various categories using fuzzy logic to find the group's path loss [3]. In the urban area of Vijayawada, India, authors [4] compare Multi-Layer Perceptron (MLP) neural network with measured path loss data. MLP has shown the right outcome prediction [4]. The authors built a path loss model using ANFIS [5]. Authors built a path loss model using ANN having site-specific parameters as inputs for the urban area [6]. Authors built a path loss model using MLP based ANN for four transmitters at 900 MHz [7]. There is no consideration of essential parameters like the %building, %road, %plain, %water, %trees in papers [4]–[7]. In [3], the authors obtained less than 8 dB RMSE between predicted and measured path loss. Mean absolute error between predicted & measured path loss for the Auto-regressive moving average(ARMA) model was 2.83 dB, whereas, for the Neural Network(NN) model, it was 0.46 [4]. The average RMSE between predicted & measured path loss for the ANFIS model is 2.3569 dBm [5]. The RMSE obtained between predicted & measured path loss is between 3-6 dB [6]. The RMSE between predicted & measured path loss is 4.85 dB [7].

In this paper, we have combined image segmentation and techniques like Fuzzy logic, ANN, and ANFIS to predict the path loss. Firstly we take a sizeable 2-dimensional satellite image of 4 cities, namely Hyderabad, Mumbai, Chennai, New Delhi, and then divide the large 2d image into many smaller images. Then we perform image segmentation using the Maximum likelihood algorithm on each smaller image. Image segmentation separates the image into separate regions containing pixels with identical attributes. We extract information such as %building, %road, %plain, %water, and %trees from each

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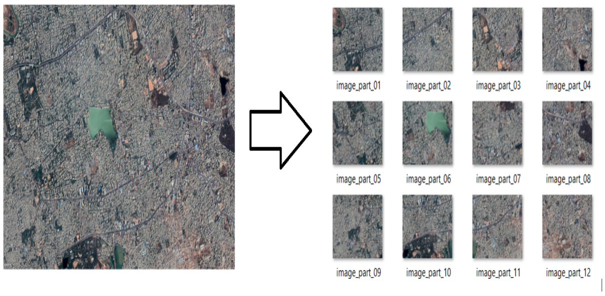

Fig. 1. Slicing of larger 2D Image into smaller Images.

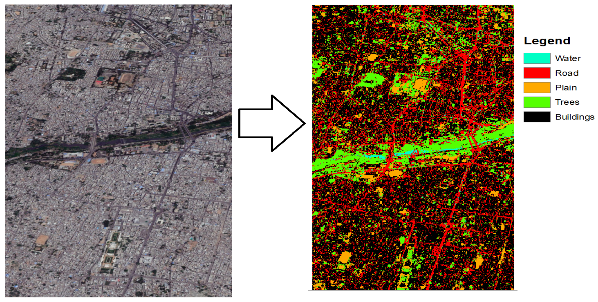

Fig. 2. An illustration of image segmentation in Hyderabad city.

smaller image using image segmentation. %Water represents the percentage of the area covered by the water bodies like the lake, sea, etc., in a sliced smaller image. %Plain represents the percentage of area covered by the flat, sweeping landmass other than roads that generally do not change much in elevation in a sliced smaller image. %Building represents the percentage of area covered by buildings in a sliced smaller image. %Trees represent the percentage of area covered by the trees in a sliced smaller image. %Roads represents the percentage of area covered by the roads in a sliced smaller image. The input average clutter height represents the average clutter height in a sliced smaller image. After that, we develop 3 different 11 input path loss models based on Fuzzy logic, ANN, and ANFIS, respectively. We find that the path loss model based on ANFIS(with image segmentation) has an RMSE of 2.16 dB, which is lowest among all the considered models. Section II describes the image segmentation. Section III gives an outline of path loss prediction using FCM. Section IV provides an overview of the path loss model based on ANN. Section V describes the path loss model based on ANFIS. Section VI gives results, and finally, Section VII provides a conclusion.

II. Image Segmentation

We have collected path loss data in Mumbai, New Delhi, Chennai and Hyderabad. The details of the measurement process are described in the paper [8]. We take a large 2-dimension satellite images of 4 cities, namely Hyderabad, Mumbai, Chennai, New Delhi and then divide the large 2d image into many smaller images, as shown in Fig. 1. We perform image segmentation using the Maximum likelihood(ML) algorithm on each smaller image and classified each smaller image into 5 classes namely water(blue), forest(green), building(black), plain(light green) and road(red). We have chosen the ML algorithm as it provides the least error [9]. Fig. 2 shows an illustration of satellite image segmentation.

III. Path Loss Prediction using Fuzzy C-Means Clustering (FCM)

The clustering method in which one piece of data belongs to 2 or more clusters is FCM. The basis of the algorithm the minimization of the following objective function:

$$\sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m}\left\|x_i - c_j\right\|^2 \tag{1}$$

Paper [10] describes all the parameters in the above equation. Algorithmic steps for Fuzzy c-means clustering:
Let $X = x_1, x_2, x_3..., x_N$ be the set of data points, C is the number of clusters, $c_1, c_2, ..., c_C$ be the centroids of each cluster and m be any real number greater than 1.

Algorithm 1 Fuzzy c-means clustering Algorithm

Input: $x_1, x_2, x_3..., x_N, C, m$
Initialize u_{ij}, membership values randomly – matrix U^0, $\epsilon = 100$.
repeat
  for $j = 1$ **to** C **do**
    Compute centroids, c_j using $c_j = \dfrac{\sum_{i=1}^{N} u_{ij}^{m} x_i}{\sum_{i=1}^{N} u_{ij}^{m}}$
  end for
  Compute new membership values, u_{ij} using $u_{ij} = \dfrac{1}{\sum_{k=1}^{C}\left(\dfrac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}}$
  Update $U^{k+1} \leftarrow U^k$
  Compute $\epsilon = U^{k+1} - U^k$
until $\epsilon < 0.01$

IV. Path Loss Prediction using Artificial Neural Network

Fundamentally, the engineering approach of a biological neuron is the artificial neuron. The artificial neuron has several inputs, but the output is one. The vast number of simple processing elements interconnect with each other and layered form this ANN [11]. In [12], the authors built a path loss model using feed-forward neural networks. The architecture used was a single-layered feed-forward neural network. This network has six inputs: distance, clutter height, altitude, elevation, latitude, and longitude. It has a single output called path

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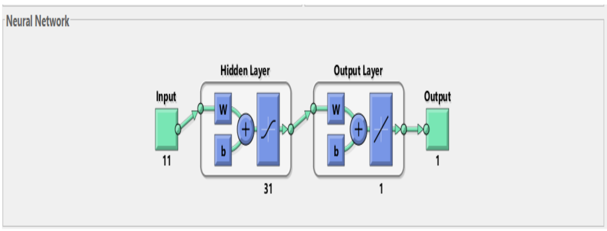

Fig. 3. A 2 layered MLP network for path loss model.

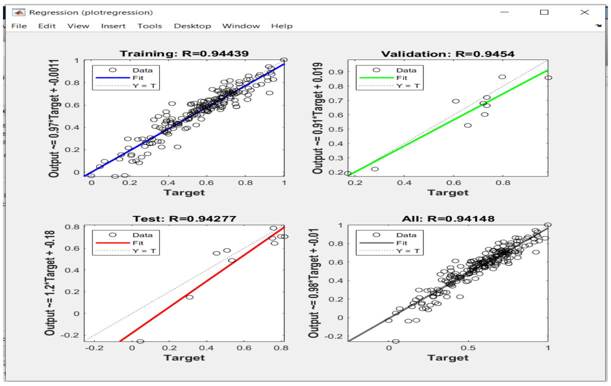

Fig. 4. R values for optimal ANN model training and validation.

loss [12]. We have built a multilayer perceptron (MLP) feed-forward network, consisting of 2 layers, with 11 inputs and one output. We used the Tan-sigmoidal function as the activation function. This ANN model's inputs are %building, %road, %plain, %water, %trees, transmitter terrain height, receiver terrain height, the distance between Tx and Rx, average clutter height, transmitter frequency, and transmitter height. Path loss is the only output of this ANN model. The feedforward back-propagation network implemented is shown in Fig. 3.

V. Path Loss Prediction using Adaptive Neuro-Fuzzy inference system(ANFIS)

ANFIS combines the merits of fuzzy systems and neural networks. ANFIS creates its structure. Foundation for constructing a set of fuzzy if-then rules is served by ANFIS

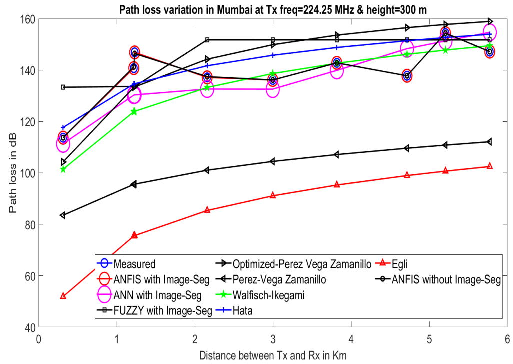

Fig. 6. The Comparison of models in Mumbai

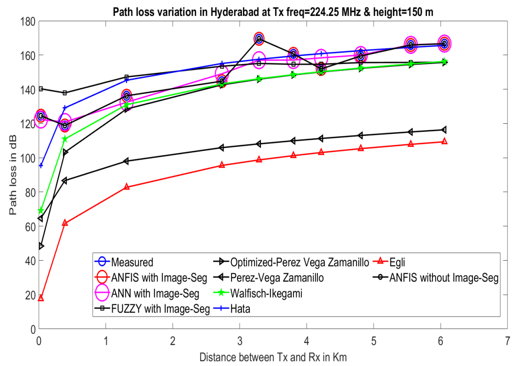

Fig. 7. Comparison of models in Hyderabad

with proper membership function to produce the specified input-output pairs. With appropriate training, created FIS is used to forecast any spun yarns. Fuzzy logic, fuzzy set, data clustering, and neural network are the main constituents of this model. We introduce ANFIS for developing the path loss model in this paper. Since we can achieve fast conversions, reduction in complexity by subtractive clustering with ANFIS, we have implemented subtractive clustering with ANFIS for the development of the empirical model [13]. Input Parameters to this ANFIS path loss model are %building, %road, %plain,

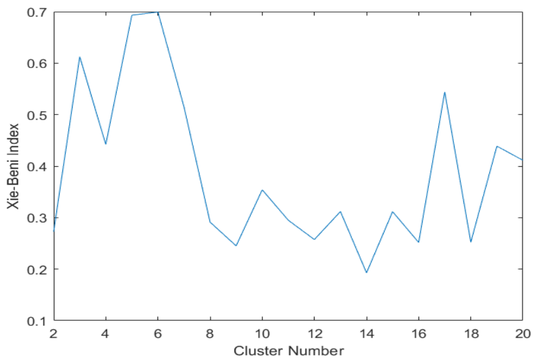

Fig. 5. The obtained Xie-Beni index values

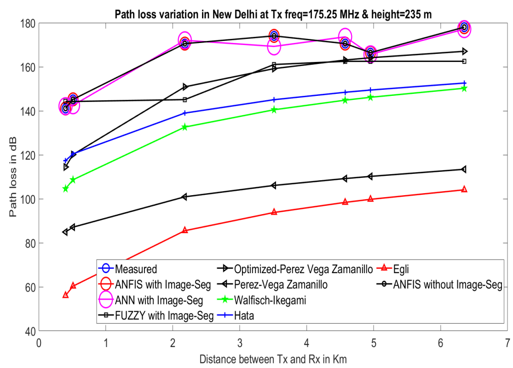

Fig. 8. The Comparison of models in New Delhi

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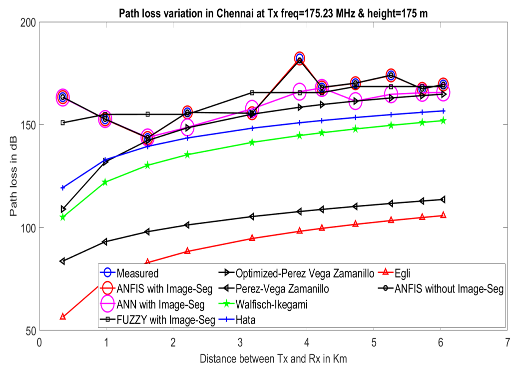

Fig. 9. Comparison of models in Chennai

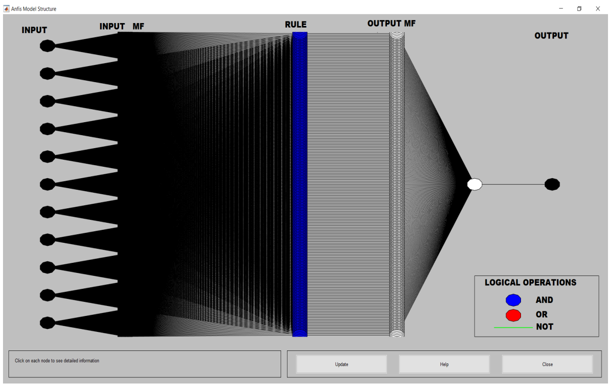

Fig. 10. ANFIS model structure

%water, %trees, transmitter terrain height, receiver terrain height, the distance between Tx and Rx, average clutter height, transmitter frequency, and transmitter height. The output of the ANFIS Model is path loss. In the article [14], we find an elaborate explanation of the underlying basic ANFIS architecture used in this paper. Fig. 10 depicts our ANFIS model structure.

VI. Experimental Results and Discussion

We have collected path loss data in Mumbai, New Delhi, Chennai, and Hyderabad. Paper [8] describes the details of the measurement process. We compared the measured path loss values for each route with the predicted path loss values obtained with ANN(with image segmentation), ANFIS(with image segmentation), FCM(with image segmentation), ANFIS(Without image segmentation) and empirical path loss models. Hata [15], Egli [16], Walfisch Ikegami model [17], Perez-vega Zamanillo model [18], and optimized Perez-Vega Zamanillo model [8] are the considered empirical path loss models. The receiver height was kept constant at 1 m above the ground throughout data collection in 4 Indian cities.

The min-max normalization procedure solved significant variations in data. The complete data set consists of 258 samples. We have trained ANFIS and FCM models using 204 samples of data. For deriving an optimal model, we varied the neurons from 1 to 50 in the hidden layer. Fig. 3 shows the optimal ANN (network architecture). For developing the ANN model, we divide 204 samples of data into 90% training, 5% validation, and 5% testing. Fig. 4 shows the degree of correlation(R). R value obtained for training was 0.94439. R value obtained for validation was 0.9454. R value obtained for testing was 0.94277. Overall, the R value is 0.94148 for the model training process. These values guarantee high prediction accuracy in an urban area. We validate ANN, ANFIS, and FCM models using 54 samples of data. Fig. 11 shows the ANFIS structure without image segmentation. The inputs for this ANFIS structure are transmitter terrain height, receiver terrain height, the distance between Tx and Rx, average clutter height, transmitter frequency, and transmitter height. The output of the ANFIS Model is path loss. We used subtractive clustering together with ANFIS for achieving fast conversions & reduction in the associated data. Paper [14] gives an elaborate explanation of the underlying basic ANFIS architecture developed in this paper. For the Fuzzy c means(FCM) based Path loss model, we found the Xie-Beni index. One of the commonly used indexes to find the cluster number is the Xie-Beni index. Xie-Beni index provides the right partition connected with the separation and compactness of clusters [19], [20]. Fig. 5 displays the variation of the Xie-Beni index with a cluster number. We find that the cluster number's optimal value is 14, as it has the least Xie-Beni index value. We initialize the center of each Gaussian membership function by cluster centers produced using the FCM algorithm. We have calculated standard deviations σ using the procedure given in [21].

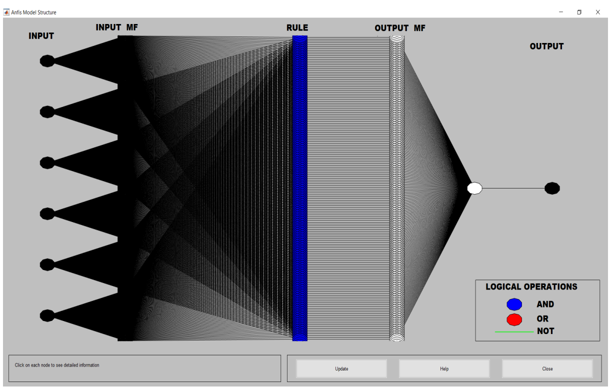

Fig. 11. ANFIS Structure without Image Segmentation

We calculate RMSE between predicted and measured path loss values using the procedure given in [8]. Fig. 6 to Fig. 9 shows the comparison of various models with measured path loss across different places in India. In Fig. 6 to Fig. 9, we find that ANFIS with image segmentation is closer to path loss's measured values. Fig. 6 shows a comparison of various models with measured path loss data in Mumbai along route-1. We find that the ANFIS model with image segmentation is very close to measured path loss data. Table I shows the comparison of various models with measured data. From Table I, we find that the ANFIS model with Image segmentation has the best

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TABLE I
COMPARISON OF VARIOUS MODELS WITH MEASURED DATA.

Details of Place and Routes	Transmitter Frequency (MHz)	Transmitter height (m)	RMSE for ANFIS (with Image Segmentation)(dB)	RMSE for ANFIS (without Image Segmentation)(dB)	RMSE for ANN (with Image Segmentation)(dB)	RMSE for Fuzzy(FCM) (with Image Segmentation)(dB)	RMSE for Optmized Perez-vega zamanillo(dB)	RMSE for Perez-vega zamanillo(dB)	RMSE for Walfisch Ikegami(dB)	RMSE for Hata (dB)	RMSE for Egli (dB)
Hyderabad(Route-1)	62.25	150	0.000	0.000	4.551	13.268	44.095	78.363	48.259	53.806	92.593
Hyderabad(Route-2)	62.25	150	0.001	0.000	4.376	9.431	26.770	67.405	33.880	41.078	77.447
Hyderabad(Route-1)	224.25	150	0.000	0.000	5.032	11.387	26.659	47.798	20.340	11.757	63.623
Hyderabad(Route-2)	224.25	150	0.017	0.000	7.363	17.556	13.556	26.182	14.006	24.717	35.764
Mumbai(Route-1)	182.25	300	0.123	0.123	5.898	6.363	15.071	49.256	21.311	14.493	67.070
Mumbai(Route-1)	224.25	300	0.005	0.229	8.209	12.345	11.448	38.113	11.070	8.069	54.271
Mumbai(Route-2)	224.25	300	0.070	0.572	7.242	14.777	27.657	47.023	26.028	16.537	69.153
Mumbai(Route-3)	224.25	300	0.035	0.072	7.758	148.218	16.850	48.778	20.912	12.092	66.812
New Delhi(Route-1)	175.25	235	0.000	0.025	2.513	12.806	17.416	62.189	31.782	25.165	78.554
New Delhi(Route-2)	175.25	235	0.003	0.019	2.094	3.926	19.381	52.386	27.301	18.479	72.811
New Delhi(Route-1)	189.25	235	0.000	0.727	3.945	9.475	11.363	52.781	22.617	14.945	69.195
New Delhi(Route-2)	189.25	235	0.000	0.547	5.079	7.921	10.203	48.555	19.897	11.613	66.360
New Delhi(Route-3)	189.25	235	0.000	1.487	2.962	5.965	12.598	50.674	22.100	13.346	68.430
Chennai(Route-1)	175.23	175	0.001	0.282	6.721	8.037	19.793	60.374	28.094	20.707	73.196
Chennai(Route-2)	175.23	175	0.523	1.025	6.856	6.744	16.499	58.791	25.506	18.312	70.922
Chennai(Route-3)	175.23	175	0.000	0.228	4.612	5.592	18.250	59.204	26.665	19.095	72.077
Chennai(Route-4)	175.23	175	0.000	0.333	5.021	13.083	9.462	54.441	19.634	13.710	65.311
Chennai(Route-5)	175.23	175	0.000	0.099	5.280	9.763	23.198	58.392	29.352	20.712	74.067
Chennai(Route-1)	189.26	175	0.000	0.081	4.294	5.376	23.953	61.061	30.893	20.808	76.751
Chennai(Route-2)	189.26	175	0.003	0.091	5.052	6.488	13.960	57.313	22.906	14.995	68.697
Chennai(Route-3)	189.26	175	0.000	0.428	4.720	9.058	23.571	65.006	32.444	23.456	78.505
Chennai(Route-4)	189.26	175	0.000	0.430	2.692	11.805	11.924	58.604	23.122	15.414	69.551
Average RMSE(dB)	-	-	0.035	0.309	5.103	15.881	18.803	54.668	25.369	19.696	69.598

TABLE II
VALIDATION OF DIFFERENT MODELS WITH MEASURED DATA.

Details of Place and Routes	Transmitter Frequency (MHz)	Transmitter height (m)	RMSE for ANFIS (with Image Segmentation)(dB)	RMSE for ANFIS (without Image Segmentation)(dB)	RMSE for ANN (with Image Segmentation)(dB)	RMSE for Fuzzy(FCM) (with Image Segmentation)(dB)	RMSE for Optmized Perez-vega zamanillo(dB)	RMSE for Perez-vega zamanillo(dB)	RMSE for Walfisch Ikegami(dB)	RMSE for Hata (dB)	RMSE for Egli (dB)
Hyderabad(Route-3)	62.25	150	10.132	9.980	28.235	15.882	38.389	69.012	40.575	45.271	84.197
Hyderabad(Route-3)	224.25	150	14.290	16.729	36.156	14.638	20.521	41.469	13.945	9.033	56.801
Mumbai(Route-2)	182.25	300	15.257	12.726	13.199	11.430	17.547	53.332	23.478	17.900	69.244
Mumbai(Route-3)	182.25	300	6.947	16.491	15.750	13.628	26.526	53.297	29.577	21.958	73.747
New Delhi(Route-3)	175.25	235	6.885	8.512	7.383	8.646	18.238	56.325	28.725	20.913	74.349
Chennai(Route-5)	189.26	175	6.325	4.934	6.829	7.757	25.211	62.936	32.509	22.417	78.459
Average RMSE(dB)	-	-	9.973	11.562	17.925	11.997	24.405	56.062	28.135	22.915	72.799

performance as it has the least RMSE of 0.035 dB. Fig. 7 shows the comparison of various models with measured data along Route-1 at 224.25 MHz in Hyderabad city. We validate or test all path loss models along routes mentioned in Table II. From Table II, we find that the ANFIS model with image segmentation has better overall performance among the considered path loss models as it has the lowest average RMSE of 9.973 dB. In this paper, overall average RMSE for ANFIS(with Image Segmentation), ANFIS(without image segmentation), ANN(with image segmentation), Fuzzy(with image segmentation), Optimized Perez-Vega Zamanillo, Walfisch-Ikegami, Perez-Vega Zamanillo, Egli, Hata models are 2.16 dB, 2.72 dB, 7.85 dB, 15.049 dB, 20.004 dB, 25.962 dB, 54.966 dB, 70.284 dB and 20.386 dB, respectively. From Table I and Table II, we find that the ANFIS model with image segmentation has the best performance as it has the overall average RMSE of 2.16 dB, which is the least average RMSE among all the considered path loss models.

VII. CONCLUSION

Buildings do not cover urban cities uniformly. Some parts of the town have large building densities, and others have smaller building densities. Similarly, some regions have large trees, and some have little tree coverage. It is necessary to know the propagation areas to apply the proper model for predicting the path loss. In this paper, we have combined image segmentation and techniques like Fuzzy logic, ANN, and ANFIS to predict path loss. We take a sizeable 2-dimensional satellite image of 4 cities, namely Hyderabad, Mumbai, Chennai, New Delhi, and then divide the large 2d image into many smaller images. Then we perform image segmentation using the Maximum likelihood algorithm on each smaller image. Segmentation separates the image into separate areas comprising of pixels with identical qualities. We extract the information such as %building, %road, %plain, %water, %trees, from each smaller image using image segmentation. After that, we develop three different 11 input path loss models based on Fuzzy logic, ANN and ANFIS, respectively. Input Parameters to all these three path loss models were %building, %road, %plain, %water, %trees, transmitter terrain height, receiver terrain height, the distance from Tx to Rx, average clutter height, transmitter frequency, and transmitter height. The input average clutter height represents the average clutter height in a sliced smaller image. The output of all three models is path loss. We compare the measured path loss values for each route with the values

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predicted by ANN(with image segmentation), ANFIS(with image segmentation), FCM(with image segmentation), ANFIS(without image segmentation) and empirical path loss models. Accuracy of each path loss the model was measured using RMSE obtained between the measured and the predicted path loss values. This paper finds that ANFIS(with image segmentation) path loss model has an RMSE of 2.16 dB, which is the least RMSE among all the considered path loss models. This paper's research results show that we can use the ANFIS based path loss model with an image segmentation for cell planning and cognitive radio as it provides an accurate prediction of path loss.

ACKNOWLEDGMENT

The author is thankful to Dr. Mohammed Zafar Ali khan of IIT Hyderabad for his helpful suggestions, support and encouragement.

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