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A Fuzzy-Logic Based Path Loss Model at 3.4 GHz for LTE Networks

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Abstract

Empirical and deterministic models have not proven to be effective in path loss predictions because of the problems of computational complexities, low accuracies, and inability to generalize. To solve these problems relating to path loss predictions, this article presents an optimal path loss propagation model developed at 3.4 GHz with the use of fuzzy logic. We introduced Fuzzy logic to accurately represent all forms of uncertainties in the data spectrum as the signal propagates from the transceiver to the receiver, thereby producing accurate results. Experimental data were collected across Cyprus at 3.4 GHz and compared with three existing path loss models. The fuzzy-logic path loss prediction model was then developed and compared with the experimental data and with each of the theoretical empirical models, the newly developed model predicted signal loss with the greatest accuracy as it gives the lowest root-mean-square error. The newly developed model is very efficient for signal propagation and path loss prediction.

Keywords

Signal Loss, Fuzzy-Logic, Machine Learning, Signal Propagation, Accuracy, Empirical, Deterministic

1. Introduction

Wireless networks have brought a great uniqueness to the world of mobile communication because of the capacity to provide adequate coverage with the use of effective propagation models [1] [2] [3] [4]. The wireless mobile networks employ high-frequency radio waves to establish communication between a base transceiver station and a mobile receiver in a way without any wired connection between them [5] [6]. There are many growing issues when it comes to wireless communication and the sustainability of such a system in which; some of them are channel capacity, noise, interference, losses in signals, frequency reuse and security of the wireless system. The major goal and objective in signal transmission are to have minimal attenuation as signals transmitted from the transmitter to the receiver.

Signal Propagation models are essential parameters employed in wireless network planning and optimization. They are very effective in interference analysis and cell parameter evaluation. Planning for a network entails using the right signal propagation model so optimization can be achieved. These models are developed principally to ensure high accuracy in signal transmission. Signal loss is developed by network engineers and professionals to estimate the path loss of the received signal as they travel from the base station to the receiver. The problem with many of these models is that they only function effectively in the environment where the field measurement was carried out and performed woefully when deployed to the other areas. For this reason, the signal propagation models face a huge difficulty when it comes to generalizing and extension for use in multiple environments. Signal Propagation measurements must therefore be carried out before any analytical model of high accuracy can be achieved.

The experimental measurements are important so there can be proper channel characterization and to provide signal parameters that will generate efficient performance and optimization. The measured signal loss will be compared with existing analytical signal loss models to determine which of the models predicts signal loss with the greatest level of accuracy and lowest coefficient of error. The validation will be done with root-mean-square error (RMSE. The world of wireless telecommunication is growing at a fast rate and the need for an optimized model is coming more to the forefront because of an increased appetite for an advanced and improved service as in the case of bandwidth by mobile subscribers; as a result, there is a high need for proper network coverage prediction [2]. In wireless radio networks, obstacles in the signal path as it travels from the transmitter to the receiver cause attenuation in signal strength which is the signal loss that must be accurately characterized for effective transmission to take place. Signal loss is the attenuation of the radio signal. The models play a very prominent role in radio frequency coverage optimization, interference analysis and also for optimized usage of the available network resources [3]. The accuracy of the propagation model cannot be overemphasized because it plays a major role in the overall system design and implementation. For network service providers to accurately determine the exact value of a signal loss, there is a need for extensive field measurements, site survey analysis and a careful parameter evaluation to represent what is best for the environment where the model is to be deployed. Many propagation models have been developed, and they fall into different categories such as empirical, stochastic and deterministic with each of them not performing optimally when deployed to other areas outside of the original place where the propagation measurement was taken. It is for this reason that this study will employ the concept of fuzzy logic because it can solve the problem of uncertainties that have existed in the other propagation models. The introduction of fuzzy logic to the subject of signal loss is to ensure greater accuracy in the network prediction model so that good quality of service will be enjoyed by mobile subscribers. The probability of call blocking and call dropping will also reduce drastically when a fuzzy-logic designed signal loss model is developed as the case in this paper. A network planner who cannot accurately determine the signal loss will ultimately produce a very much expensive network or a network of low quality [5].

The contributions of this paper are given below:

- Experimental studies were conducted in Cyprus at 3.4 GHz. Signal strength was measured in rural, suburban, and urban areas. The path loss was then computed.
- The predicted path loss for SUI, ECC-33 and free space empirical models were computed.
- The fuzzy-logic-based path loss model was then developed and compared with the experimental data collected and other empirical models. The fuzzy-logic path loss prediction model produced optimal results.

The remaining aspect of this work is structured as follows; Section 2 presents the materials and methodology adopted, including the empirical models. Results and discussion are given in Section 3 and the conclusion is presented in Section 4.

2. Materials and Methodology

The fuzzy-logic designed signal loss model articulated in this article will follow a systematic approach. Field measurements were collected across 6 base stations in Cyprus. The measured signal loss will be compared with existing analytical propagation models and validation will be done with the root-mean-square error (RMSE). The performance of the developed fuzzy-logic-based signal will also be compared with the performances of the existing signal loss propagation model and the results will be shown in section three of the paper.

2.1. Experimental Study

The signal losses measured were obtained from the experimental study carried out at 6 base stations in Cyprus with the aid of a driving test. The field measurements were done in conjunction with Vodafone Telecommunication company in Cyprus, with measurements collected across rural, suburban and urban areas so as to ensure a wide class of representation. The areas in the cities are categorized as urban (metropolitan), while some others less congested are classified as sub-urban and the areas closer to what is obtainable in free space where a dominant line of sight exists are classified as flat/ open (rural) areas because of the network congestion in the place, cell size and other technical factors. Field measurements were collected at a distance of 100 m - 2.0 km with intervals of 100 m.

The field experiments were conducted with test mobile system (Tems) 16.3 investigation tool coupled with other equipment, all housed in a vehicle during the driving test. In a portable Lenovo laptop computer, a fixed GPS was used to ascertain the exact location at a particular point as signals travel from the transmitter to the receiver. A mobile phone of a height of 1.5 m serves as the mobile receiving station. Also, a USB connector to connect the device to the Laptop, serial cables, and a vehicle. All the drive test equipment and devices were connected to the Lenovo Laptop inside the vehicle and signal strength was measured at 3400 mHz at an interval of 100 m starting from 1 km - 2.0 km.

Signal strength was measured across 6 base stations in Cyprus at an operating frequency of 3.4 GHz. Two base stations in Kyrenia, two in Lefkosia and two in Magusa representing urban, suburban, and rural areas respectively. The signal strength measurement is subtracted from the effective isotropic radiated power (EIRP) to determine the exact signal loss at each measuring distance. Figure 1 gives the interface test equipment mobile (Tems) system during drive test.

2.2. Selected Signal Loss Models

Some existing signal loss models were selected and compared with the measured data so as to check which of them agreed well with the field measurements with little or no error. There are so many of these models, but the few prominent ones will be examined and used in this article.

2.2.1. Stanford University Interim Model

The Stanford university interim model is applicable for signal propagation below 11 GHz and used for both fixed and wireless mobile system.

$$\text{Signal loss} = B + 10\gamma \log_{10}\left(\frac{d}{d_0}\right) + K_f + K_h + S_f \quad \text{for } d \succ d_0 \tag{1}$$

$$A = 20\log_{10}\left(\frac{4\pi d_0}{\lambda}\right) \tag{2}$$

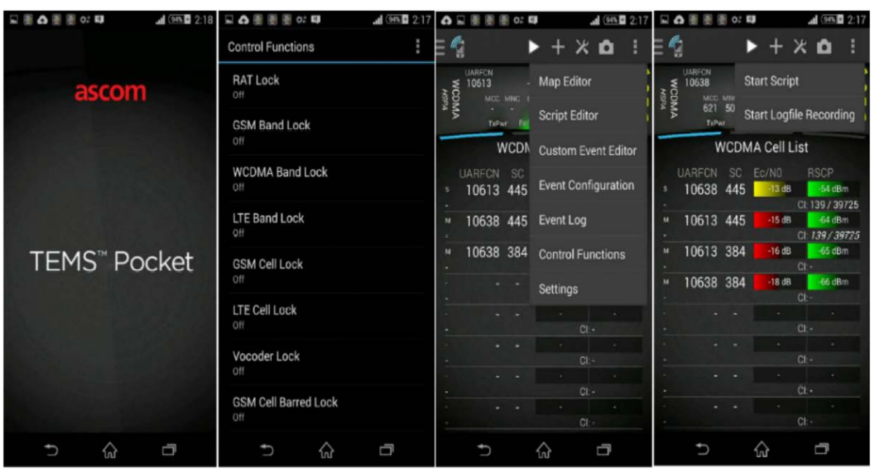

Figure 1. Drive test at 3.4 GHz.

$$\gamma = a - bh_b + \frac{c}{h_b} \tag{3}$$

$$K_f = 6.0\log_{10}\left(\frac{f}{2000}\right) \tag{4}$$

$$K_h = -10.8\log_{10}\left(\frac{h_r}{2000}\right) \quad \text{for terrain } A \text{ and } B \tag{5}$$

$$K_h = -20.0\log_{10}\left(\frac{h_r}{2000}\right) \quad \text{for terrain } C$$

B in the equation is given as the free space signal loss while d represents the distance in km from the transmitter to the receiver a, b, c represents terrain parameters for urban, suburban and rural areas respectively.

2.2.2. ECC-33 Model

This signal loss propagation came into existence as an improvement of the Okumura model. All the inadequacies of the initial model were reviewed in the development of the ECC-33 model [6] [7] [8].

$$S_L(\text{dB}) = A_{FS} + A_{BM} - G_B - G_R \tag{6}$$

$$A_{FS} = 92.4 + 20\log_{10}(d) + 20\log_{10}(f) \tag{7}$$

$$A_{BM} = 20.41 + 9.83\log_{10}(d) + 7.894\log_{10}(f) + 9.56\left(\log_{10}(f)\right)^2 \tag{8}$$

$$G_B = \left(\log_{10}\left(\frac{h_b}{200}\right)\right)\left(13.958 + 5.8\left(\log_{10}(d)\right)^2\right) \tag{9}$$

$$G_R = \left[42.57 + 13.7\log_{10}(f)\right]\left[\log_{10}(h_r) - 0.585\right] \tag{10}$$

where A_{FS} represents the free space attenuation, is the median signal loss, is the base station height gain factor, is the mobile station antenna gain factor, f is the frequency in GHz, d is the distance of separation between the transmitting station and the mobile station in km.

2.3. Fuzzy-Logic Path Loss Model

Fuzzy-logic is all about precision and accuracy because some parts of the system cannot be analyzed critically if we go by the existing analytical signal loss models. Fuzzy logic is all about the need to reflect all parts of the system in a very accurate way. The fuzzy-logic designed signal loss model designed in this article employs fuzzy set theory in which two variables like frequency are members of a set with some degree of membership. It is very useful in the design of signal loss models because it can effectively represent non-linear systems which are what is obtained in a typical urban environment where it is very difficult to have a line of sight. The type 2 fuzzy logic will be adopted in developing our signal loss model because the IF-THEN rules will be very useful in achieving efficient system design. All the details of the propagation environment that will step up the accuracy of the model are converted into the type-2 fuzzy set by the fuzzifur and later inference by the IF-THEN depending on the input and output of the signal loss model [9] [10].

In [11]-[20], machine learning techniques were applied to path loss modeling to achieve greater accuracy in predictions. The machine learning algorithms yielded optimal results for empirical and deterministic models.

The fuzzy interference system is such that the behavior of the system that controls the input and the output variable is controlled by a set of rules A, which provides a strong correlation to the development of an accurate signal loss model than the existing ones. The rule used in the development of our signal loss model is specified as follows:

$$\text{if} \quad y = B \text{, then} \quad z = C$$

$$100 \leq f \leq 3400 \text{ GHz}$$

$$1.5 \leq h_r \leq 8 \text{ m}$$

$$100 \leq d \leq 2 \text{ km}$$

if $y = B$, then $z = C$ When a set of input variables are read, then each of the rules that has any degree of truth is added to the membership function as the fuzzy logic system (FLS) approximately represents both the input and the output variable.

The input variables in the signal loss model have received signal strength and the distance while the output is the signal loss. We adopted a Gaussian membership function for the two input variables and a triangular membership function for the output variable. The deffuzification process is very important because the fuzzy quantity needs to be converted back to the crisp entity. The fuzzy-logic toolbox in MATLAB 2016RB was used for the simulation and a 16 -based rule system was adopted because of its simplicity.

3. Results and Discussion

The Path loss of the received signal at any point from the transmitter to the receiver is given as follows:

$$\text{Path loss} = \text{EIRP} - \text{signal strength} \tag{11}$$

The effective Isotropic Radiated Power (EIRP) is 57.6 dBm and the signal loss becomes.

$$\text{Path loss} = 53.5 - \text{Received power}$$

The two inputs to the fuzzy-logic are distance and the received signal strength. From the fuzzy-logic design, the rule view of the model is shown in **Figure 2**.

The signal loss is largely dependent on the two parameters which are a function of distance and the received signal strength. To model an accurate and effective signal loss, the network providers must do it as a function of the two parameters. The input parameters of the design are given in **Figure 3**.

The surface view of the model in each of the areas considered will be shown in the next section and it reflects the large signal loss in urban areas because of the non-existent dominant line of sight.

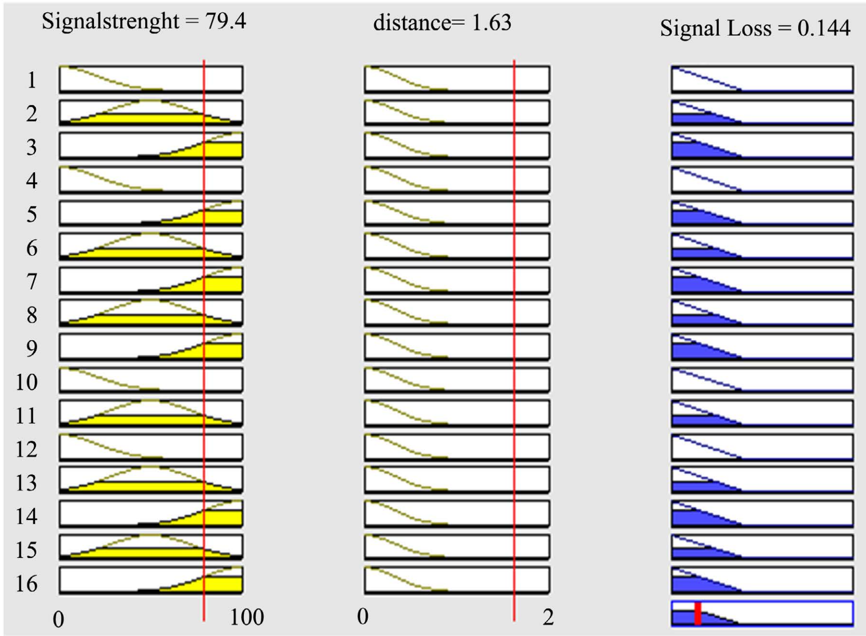

Figure 2. Rule view of fuzzy based signal loss model.

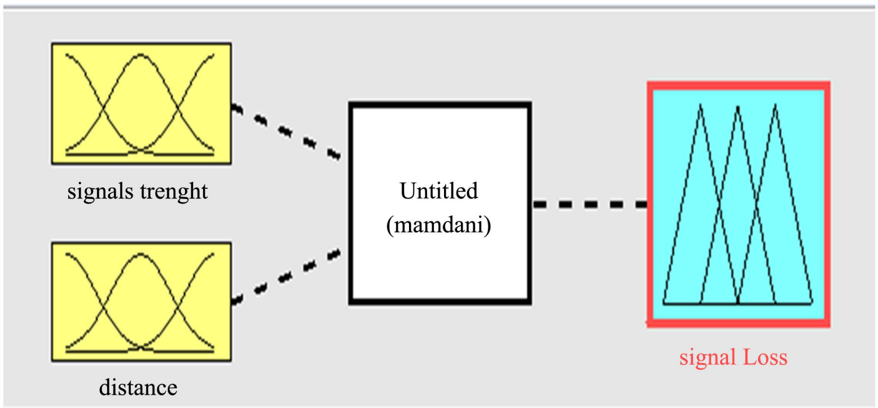

Figure 3. Inputs and output parameter of the design.

Figures 4-6 shown give the surface plots of the fuzzy-logic signal loss model and it is evident from the plots that the signal loss is largely dependent on the distance and the signal strength. The signal loss is smallest in the rural areas where there is a little obstruction in the signal path from the transmitter to the receiver and where a clear dominant line of sight exists.

The performance of the fuzzy-logic signal loss model was compared with the experimental study and existing propagation models in rural, suburban and urban areas as shown in **Figures 7-9**. The newly developed fuzzy-logic signal loss model predicts signal loss in Cyprus very accurately as it gave signal loss very close to experimental data. The performance of the new model was far better than the existing models because of the ability of fuzzy-logic to accurately model any form of uncertainties. That is why the new model gave the signal loss accurately like the field measured data.

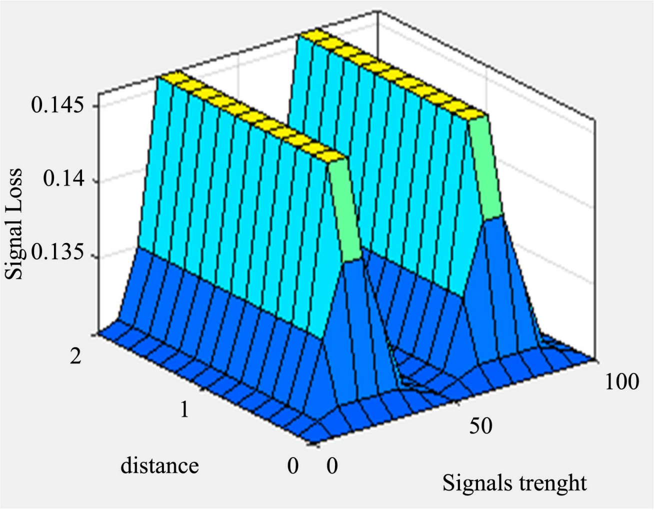

Figure 4. Surface view of the signal loss in rural area.

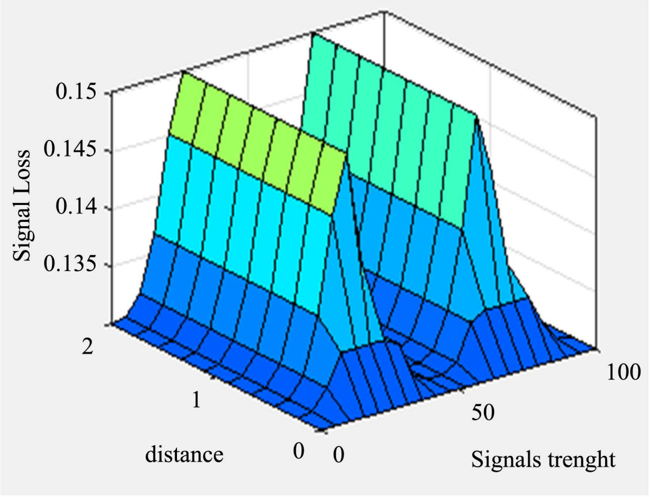

Figure 5. Surface view of the signal loss in urban area.

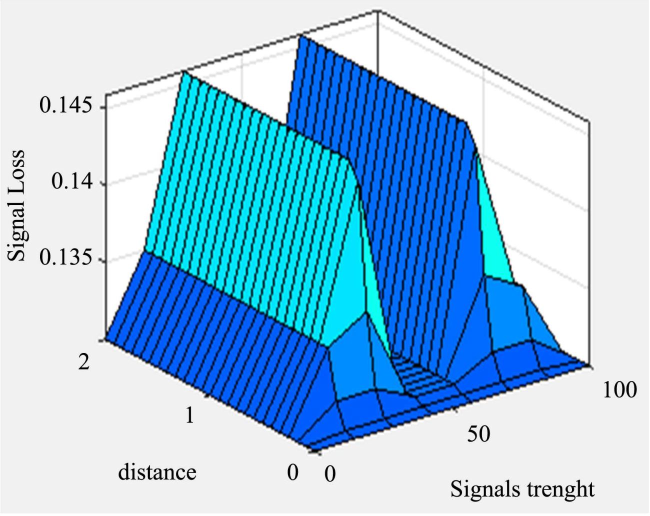

Figure 6. Surface view of the signal loss in suburban area.

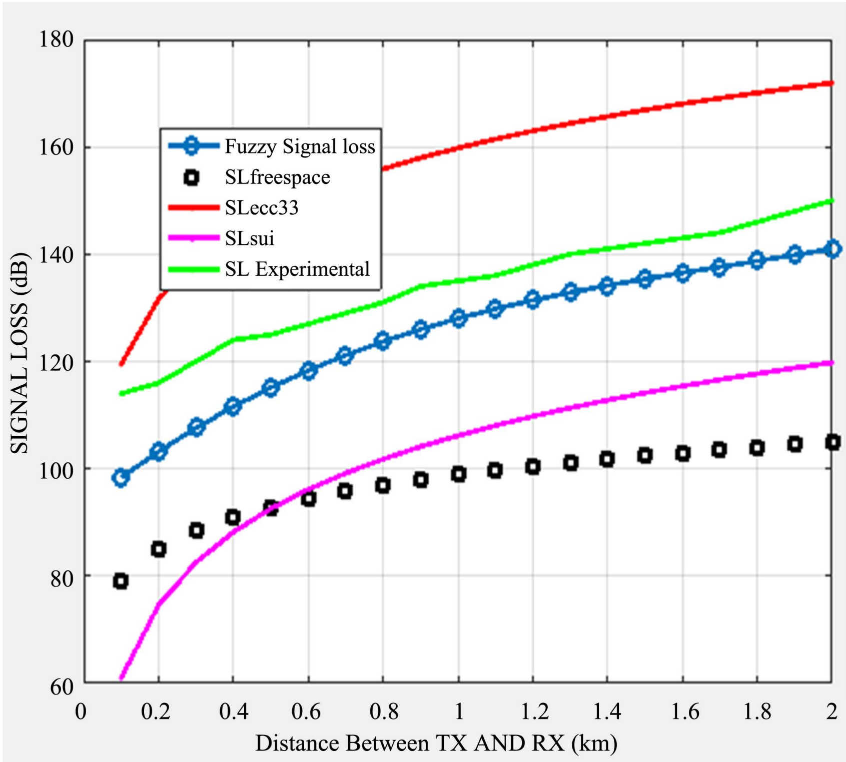

Figure 7. Signal loss of experimental data, the newly developed fuzzy-model and the existing models in urban areas.

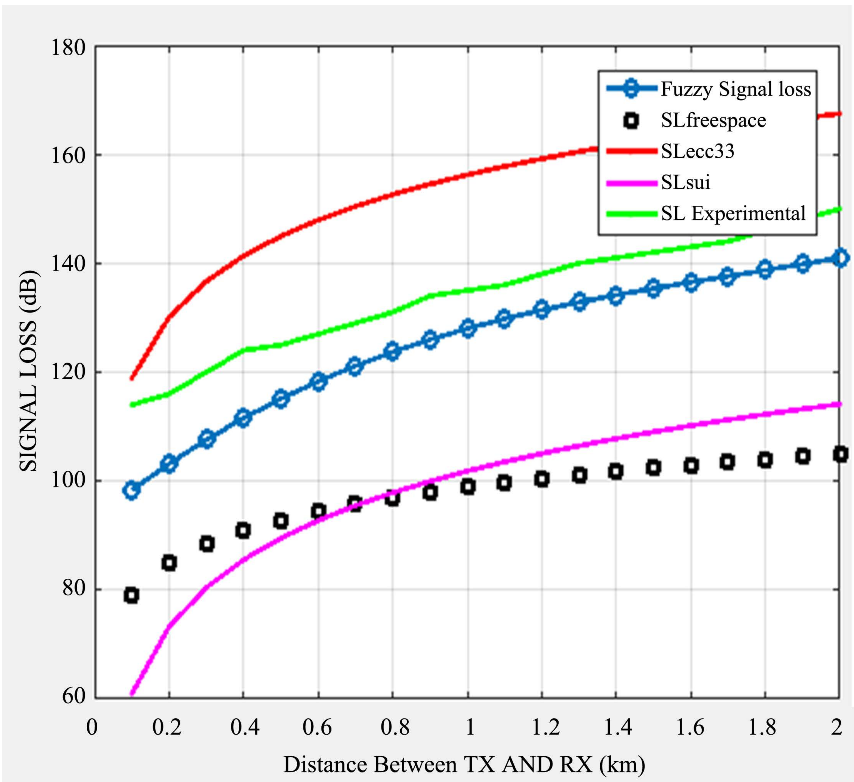

Figure 8. Signal loss of experimental data, the newly developed fuzzy-model and the existing models in suburban areas.

Figure 7 shows that the new fuzzy-logic model predicts signal loss accurately than the other existing models examined. The graph of the fuzzy-logic model is the closest to the experimental data. Signal loss is highest in urban areas because of the many obstructions in the signal path from the transmitter to the receiver.

Figure 8 shows that the new fuzzy-logic model predicts signal loss accurately than the other existing models in suburban areas in the locations examined. The graph of the fuzzy-logic model is the closest to the experimental data.

Figure 9 shows that the new fuzzy-logic model predicts signal loss accurately than the other existing models in rural areas in all locations examined. The graph of the fuzzy-logic model is the closest to the experimental data. Signal loss is highly reduced in all base stations in rural areas because there is a dominant line of sight.

In Figures 7-9 and Table 1. The measured path loss was compared with the predictions made by SUI, ECC-33, and free space models. The measured path

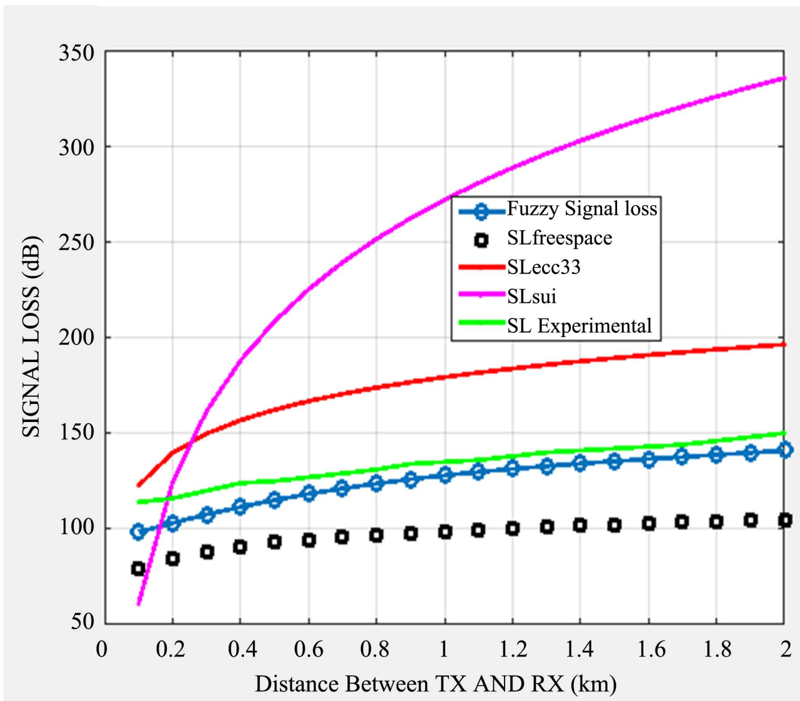

Figure 9. Signal loss of experimental data, the newly developed fuzzy-model and the existing models in rural areas.

Table 1. The RMSE values for the different signal loss models.

Signal loss Model	Rural	Suburban	Urban
ECC-33	8.59	9.44	8.02
Free space	7.89	8.96	5.92
Fuzzyy-logic model	2.96	3.84	4.78
SUI	22.62	16.94	14.65

loss was also compared with the developed fuzzy-logic prediction model. In rural, suburban, and rural areas, the fuzzy-logic predicted path loss accurately and gave path loss closest to the measured data. The other theoretical models over-predicted path loss. The fuzzy-logic path loss prediction model produced the lowest values of RMSE across all the investigated environments.

4. Conclusion

The study has examined path loss prediction models in wireless signal propagation. We developed a fuzzy-logic-based signal loss model at an operating frequency of 3.4 GHz. The developed model was compared with the other existing models and it predicted signal loss with the lowest root-mean-square error. The new model has RMSE values of 2.96 dB, 3.84 dB and 4.78 dB in rural, suburban and urban areas respectively. The other existing models over the predicted signal loss. This has clearly shown the inadequacies of empirical and deterministic models in path loss predictions because they cannot be generalized. An empirical path loss model that worked for one location may poorly predict path loss when deployed in another environment. This is the motivation for the introduction of fuzzy logic to path loss prediction. The new model performs best when compared with the experimental signal loss in Cyprus and can therefore be used for signal loss prediction and data analysis. The concept of fuzzy-logic used in the development of the model made it more efficient and accurate than the other existing empirical models.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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