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Predicting WSN packet loss using machine learning: Applications in solid surroundings

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Abstract: The effectiveness of wireless communication systems exposed to radio propagation in their environment is shown by path loss, a key performance metric. For a long time, researchers have used the correlations they proposed to calculate route loss for waves moving across different environments with few operational factors. To swap out the log-normal shadowing model for route loss calculation on concrete surfaces, this study presents a new model based on weights of artificial neural networks. In the training phase, the neural network was provided the data of the physical separation between the transmitters and receivers of the wireless sensor nodes (d) and the radial angle of the reception node's position (♀) as the target variable, path loss. Then, by utilizing the weights of the network, a novel PL prediction formula was developed. When tested across all ranges of experimental data, this formula outperforms the log-normal shadowing model, the FSPL model, and the Two-Ray model in predicting the average PL in concrete surfaces, with mean absolute deviation values of 0.51%, 4.1%, 40.58%, and 28.79%, respectively.
Keywords: *Artificial neural network, Packet Loss Model, Path loss, Propagation characteristics, Wireless Sensor Networks.*

1. Introduction

This paper explains how attenuation, or the weakening of a radio signal, can impact the efficiency of wireless communication systems; in particular, how the farther away receivers are from the transmitter, the more attenuation the signals will experience. Physical impediments during signal transmission attenuate the signal, which in turn creates secondary signaling pathways, which can be characterized as deviation, reflection, or dispersion signals, and alters the receiving signal's intensity. Since most wireless service is conducted domestically and internationally, there is an immediate need for higher data speeds in both settings. For this reason, path loss (PL) models for WSN evaluation have been actively pursued by researchers. When it comes to wireless network applications, the model for determining the value of track losses is crucial for pinpointing the positions of wireless nodes. Factors like residential structures, trees, and other such features influence the accuracy of the nodes' positions [1-4]. Furthermore, positioning applications for wireless sensor nodes help with the efficient distribution of nodes in wireless sensor networks, which improves battery life and guarantees uninterrupted communication. Two-Ray and Free Space Path Loss are two popular models for determining path loss, and they are applicable both indoors and outdoors. Both methods rely on assumptions, which might lead to erroneous outcomes when applied to certain scenarios. While the FSPL model presumes that the transmitter and receiver antennas are in direct line of sight (LOS), the Two-Ray model assumes that the Earth is flat and conductive, and that the distance between the transmitter and receiver is significantly greater than the height of the antennas' positions from [5-11].

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In order to enhance the propagation of WSN nodes in various environments, the researchers have offered a number of experimental models. To illustrate the point, two studies were reported in Otero, et al. [12] that examined path loss models using received signal strength (RSSI) for WSNs deployed in sparse and tall grass environments. We found a path loss exponent (PLE) of 3.34 in a scattered environment and 2.55 in a long grass environment. Data collected from a WSN functioning in such a context was used to create the model shown by Eq. (1). the path loss at 1 meter, the path loss exponent, and the mean value of the standard deviations are 64.84 dB, 3.21 dB, and 2.19 dB, respectively, where d is the distance between the transmission and reception antennas and $PL(dr)$ is the path loss.

$$PL(d) = PL(d_r) + 10\alpha \log\left(\frac{d}{d_r}\right) + X_\sigma \qquad (1)$$

In a similar vein, Sabri, et al. [13] presented experimental and conventional models for WSN scattering in sandy and dense forest environments, with an average path loss (PL) of 3.42 and 4.02, respectively. The authors state that the absence of direct line-of-sight between the sending and receiving nodes is the main cause of the rise in PL. Another factor that contributes significantly to the formation of reflected waves is the flatness of the Earth [14].

Using machine learning capabilities for communication has recently been a topic of research. In the field of wireless communications, deep learning has been employed to assess path losses, estimate channels, identify modulation, and code channels. Incorporating deep learning simplifies the radio propagation models needed to operate and install sophisticated wireless networks, such 5G networks, in diverse contexts [15-21].

After being trained on a massive dataset acquired over a year from a 2.4 GHz wireless sensor network, the path loss model given by Zhang, et al. [22] demonstrated excellent accuracy. The dataset included tests of the following machine learning candidate algorithms: Neural Networks, adaBoost, K-Nearest-Neighbors, and Random forests. Of the models that were considered, Random Forest produced the least amount of inaccuracy. Many famous legal and experimental models were tested against this one, including Free Space, Level Earth, Weissberger, ITU-R, and COST235, to see how accurate it was. Consequently, the machine learning methods reduced average prediction errors by 37%, surpassing the performance of the experimental and legal models.

When assessing the efficiency of a short-range communications network, channel metrics like package dropping and path loss are crucial. Numerous academics have taken an interest in this issue; for example, in Idogho and George [23] they offer a model that uses several layers of a neural network to determine these values. Highways, residential areas, and rural areas were among the many scenarios in which the suggested forecast model surpassed experimental models, according to the study. Also, when compared to the statistical model, the suggested model produced more accurate predictions. A study was published in Wu, et al. [24] that aimed to build linear track loss models for wireless sensing networks that operate in complicated environments. Three primary methods have been used to model track loss using machine learning: basic component-supported feature selection, divergence analysis based on the Gussian process, and synthetic neural network-based multidimensional regression (ANN). We have simplified the learning model and decreased the amount of data sets by using component-supported feature selection. According to the results, the suggested path loss and shading models outperform the natural shade model and the more conventional linear track loss model in terms of accuracy and adaptability. Using a variety of frequencies, another analytical work was published by Alrubaie, et al. [25] that utilized artificial intelligence to determine route loss in suburban and urban settings. A model was developed to forecast the amount of artificial neural network (ANN)-based track loss in a multi-wall environment. The model took into consideration frequency, distance, ground attenuation, and wall variables. The results demonstrated that the accuracy of the suggested model's prediction is determined by the distance between the transmission and reception nodes, which is the key factor determining signal attenuation. Further analysis revealed that the suggested ANN model achieved superior prediction accuracy when compared to the Two-Ray, CI PL, and Gaussian process models.

More study is required to understand how to harness AI skills to construct accurate and actionable models in varied situations, notwithstanding these studies. Using the parameters of artificial neural networks trained in a certain kind of setting, this study intends to create prediction models. In addition to being tiny, having straightforward programming, and not requiring neural networking software, this model is also feature-rich. Our source for this empirical data will be the work of Elmezughi, et al. [26] which focuses on lane loss in a concretized surface environment. An artificial neural network will examine and analyze the data in order to generate a prediction model using the weights of the network. It will also be compared to the free-space path loss model, the Tow-Ray model, and the normal-log model given by Elmezughi, et al. [26] in order to assess the novel model.

2. Method

2.1. Data Preparation

The following succinctly summarizes the approach and technical specifications utilized by Elmezughi, et al. [26] for the collection of empirical data:

- Using 1925 MHz frequency to conduct tests instead of 2.4 GHz to avoid interference within the 2.4 GHz ISM range.
- The target environment is characterized by many concrete buildings.
- The transmission knot was installed at a center with half-way trains (5, 10, 15, 20, 25, 30, 35, and 40 meters).
- While the received signal intensity readings were taken on the perimeter of those circles in 16 radial directions and at a separation angle of 22.5o.
- The height of antennas with multi-directional radiation patterns to be 20 cm above the Earth's surface.
- Total recorded data: 300 readings for 128 test points.
- The large amount of data recorded gives greater accuracy in statistical aspects. Table 1 shows 128 test points for the value of path losses for the signal sent.

According to the above, Alsayyari, et al. [14] researcher team provided a model for calculating the loss of path for a wireless network spread in a concrete surface environment. Many data points have been collected for the signal received, and the characteristics of the log-normal shadowing model have been adjusted to provide a more accurate model for calculating the loss of path. The proposed model was compared with the path loss models of long grass and other scattered tree environments presented in previous works. In addition, the comparison between the proposed model and common-use path loss models such as the free space path loss (FSPL) and the Two- ray path loss showed that the two models were inaccurate in predicting the amount of loss of path for a wireless network spread in a concrete surface environment [26].

2.2. Design and Training of Ann

Many applications in the real world have been successful in using neural networks as an approximate method for non-linear problems. The fast algorithms rely on well-established methods to improve the number, such as Levenberg-Marquardt (LM). Four indicators are used as tools for assessing network performance and clarifying error rates: average square error (MSE), determining factor (R^2), and average absolute error (MAE). The following Eq. (2) – Eq. (4) are used to develop these measurements: [25, 27].

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(T_i - N_i)^2 \qquad (2)$$

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|T_i - N_i| \qquad (3)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(T_i - N_i)^2}{\sum_{i=1}^{m}(N_i)^2} \qquad (4)$$

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where T_i is the target result for i in the training data, N_i is the actual network result for i, and m is the total number of training data points. To determine the relative importance of a given entry factor i, use the following Eq. (5), developed by Olden, et al. [28].

$$Imp(i) = \sum_{i=1}^{m} IW_{ih(x)} OW_{ho(x)} \qquad (5)$$

The weight of the connection between the input and output parameters i, as well as the hidden neuron x, is indicated by $IW_{ih(x)}$ and $OW_{ho(x)}$, respectively. The total number of hidden neurons is given by m, and the hidden neuron's index number is x. *Imp(i)* represents the relative significance of parameter i. In the current study, we employed Eq. (5) to determine the relevance of each suggested network input parameter.

Table 1 presents the data set used for network training, while Table 2 provides a brief summary of their respective ranges. The input vectors of the network are the distance between the transmission and reception antennas (d) and the radial angle (θ) of the reception node site, while the output vector is the loss of path (PL).

Table 1.
Imperial path loss measurements in [DB] for 128 locations [26].

Radial No.	Radial angle (θ) degree	Distance (d)							
		5m	10m	15m	20m	25m	30m	35m	40m
1	0	93	100	106	112	115	116	120	120
2	22.5	92	100	106	111	114	116	120	120
3	45	91	97	103	107	111	114	118	119
4	67.5	89	98	102	107	111	115	117	118
5	90	88	97	102	107	113	114	118	119
6	112.5	90	98	103	106	112	114	117	118
7	135	90	98	103	107	114	115	118	116
8	157.5	90	99	103	108	112	112	116	117
9	180	89	99	104	107	112	115	115	115
10	202.5	86	96	101	105	109	113	114	113
11	225	86	95	101	106	110	112	115	114
12	247.5	86	95	100	103	107	112	114	114
13	270	86	94	100	104	107	112	114	114
14	292.5	87	95	100	105	109	111	113	113
15	315	86	95	100	104	109	112	114	114
16	337.5	88	96	101	107	108	112	114	114
Avg. Path Loss (dB)		87.8	96.3	103	105.82	109.9	112.9	114.3	116

Table 2.
The experimental data ranges that were utilized to train the network.

Radial angle θ (Degree)	Distance (m)	Path loss (dB)	Avg. path loss (dB)	Reference
0 - 337.5	5 - 40	86 - 120	87.75 - 116.2	Alsayyari A. et al. (2015)

MATLAB software was used to create a computer application (Matlab User's Guide, Copyright, R2017b). During training, a hidden layer of ten neurons was employed to get more accurate results. The hidden layer neurons sum the weighted inputs and transfer the product to the output neuron or nearby neurons using a non-linear activation function. By normalizing the data, we can better assess the relationship between the two sets of parameters (dependent and independent). Both inputs and outputs have been normalized to the interval [-1,1]. Normalized versions of the input and target vectors were fed into the network during training, which resulted in the network being more accurate. There is no need to use any additional patterns when training the ANN. The objective of an ANN is to arrive at an accurate estimation of the internal values in accordance with statistical values; the training can be accomplished with an adequate amount of data. Finally, the network was put to the test with the aid of the test samples set once the training process was finished without a hitch.

3. Model Generation and Evaluation

The research used 128 data points from route loss test points to create a 2-10-1 network with a single hidden layer for path loss prediction, Figure 1. The LM technique used to train the network was combined with Tansig and Pureline activation functions in the hidden and output layers. The LM method was selected as the most efficient because of its low error rate and fast prediction speed. The network's performance in training, validation, and testing environments is presented in Figures (2-4) respectively. Table 3 provides an analysis of the effectiveness of the ANN in terms of the linear correlation coefficient (R), Mean Squared Error (MSE), Normalized Mean Squared Error (NMSE), Minimum Absolute Error, and Maximum Absolute Error, as well as the Mean Absolute Error (MAE) between the empirical data sets and the neural network outputs.

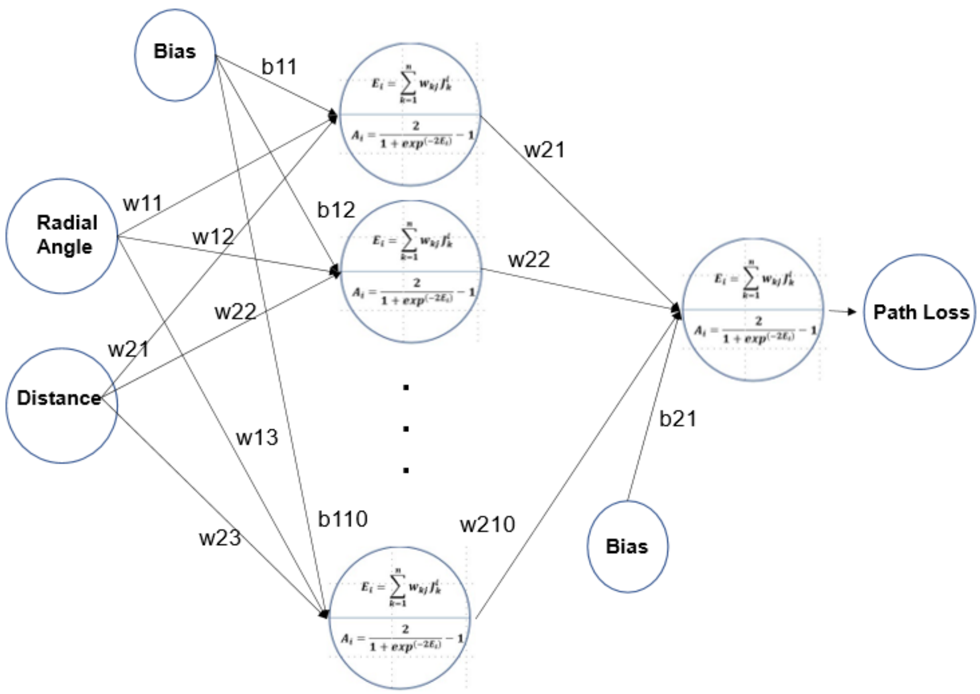

Figure 1.
The proposed 2-10-1 ANN network design.

Table 3.
Ann model performance on test phase.

Performance Metric	
R	0.993
MSE	0.688047782
NMSE	0.00052127
Min absolute error	0.000131104
Max absolute error	2.426372211
MAE	0.65765727

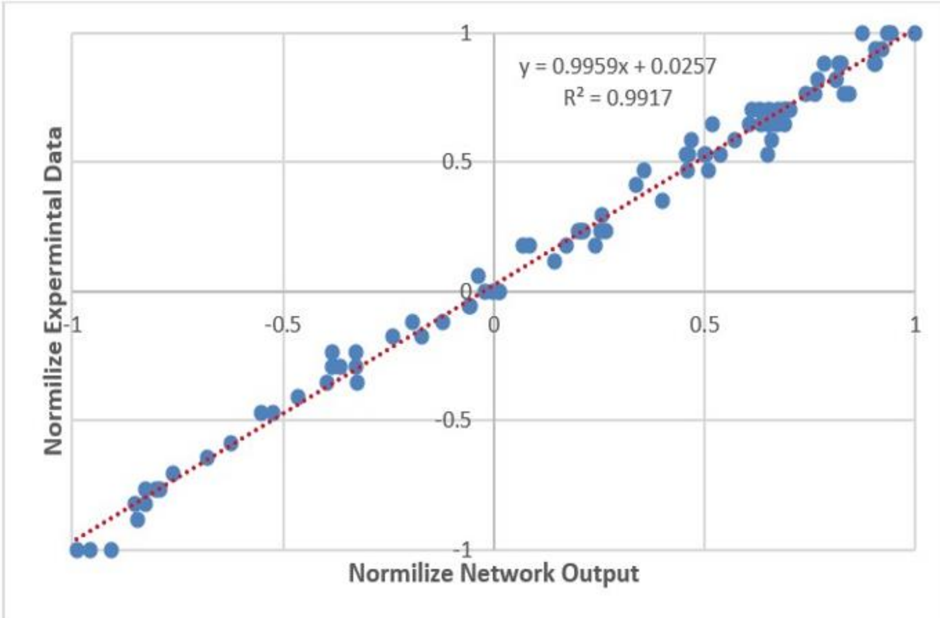

Figure 2.
The network's performance for the training phase.

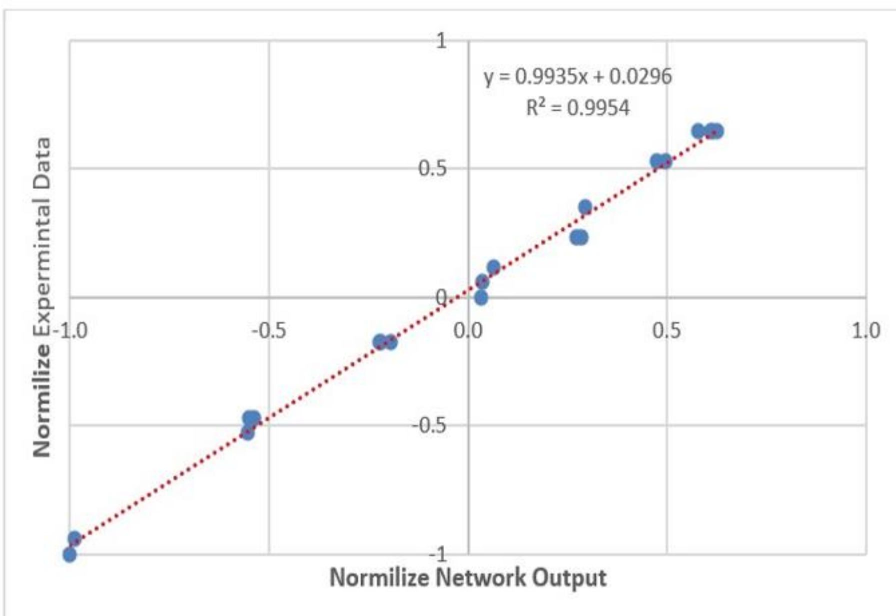

Figure 3.
The network's performance for the validation phase.

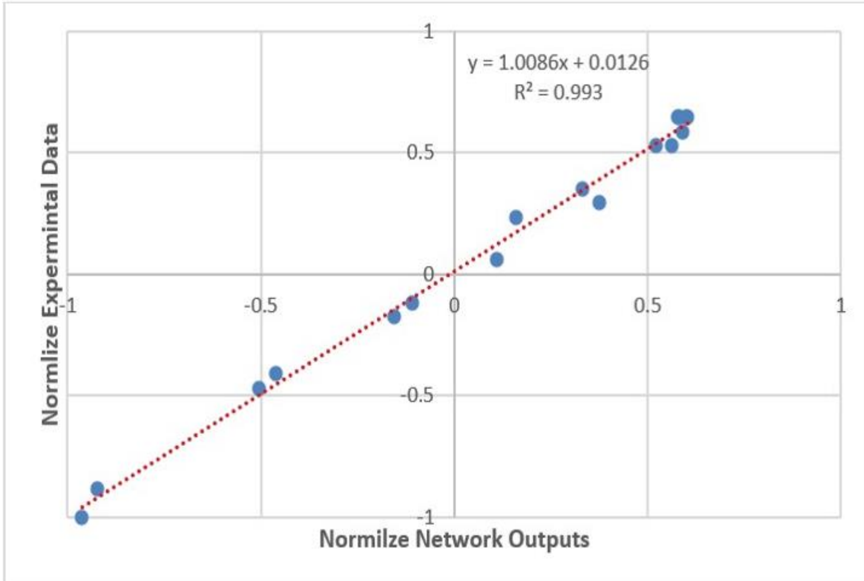

Figure 4.
The network's performance for the testing phase.

The mean square error (MSE) that occurred during the training phase as well as the verification and testing procedures shown in Figure 5. At the 16th round of repeat network training, the error appeared almost identical to the test and verification paths, and no excessive processing appears to have occurred, so the results can be considered acceptable at this round. In addition, at the 16th round of network training, where the performance of validation is at its highest level, the training is terminated. The decrease in MSE with repeated training demonstrates that the network acquires knowledge.

When the mean square error (MSE) reached its lowest value, the neural network weights shown in Table 3 were extracted. Through the stimulation function used in the hidden layer and the weighing of the grid (Eq. (6) and Eq. (7)), we can create a model for predicting track loss as shown in Eq. (9) where E_i can be extracted from Table 4.

$$A_i = \frac{2}{1+\exp(-2E_i)} - 1, \quad i = 1:10 \qquad (6)$$

$$y_i = 0.396148759\,A_1 - 1.452598172A_2 - 0.298445076A_3 + 0.065692319A_4 + 0.037979556\,A_5 + 0.008010673A_6 + 0.1364397761A_7 + 1.8278787761A_8 - 0.249978603A_9 - 0.071826287A_{10} - 0.76564 \qquad (7)$$

$$PL|_{h=0.2m} = f(\theta, d) = \left((\mathrm{y}_i - \mathrm{y.ymin})/\mathrm{y.gain}\right) + \mathrm{y.xoffset} \qquad (8)$$

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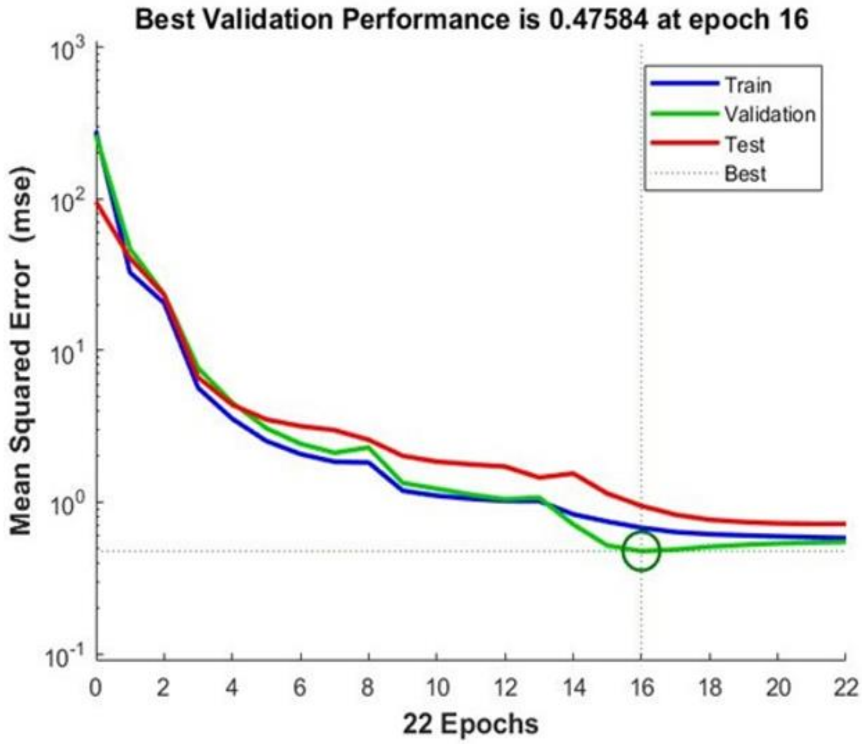

Figure 5.
Illustrates the performance of the network during the various epochs.

Table 4.
Displays the weight values that were determined by the LM method using 10 neurons.

$E_i = w_{i1}d + w_{i2}\theta + b_i$			
i	W_{i1}	W_{i2}	b_i
1	-0.62302	-1.82554	2.158872
2	-0.34997	-0.43338	0.651882
3	2.316744	0.324739	-0.17349
4	-5.63505	2.038106	1.815029
5	-1.42184	8.25101	-0.40928
6	-3.64266	3.674756	-0.14819
7	3.442881	0.591924	1.430197
8	0.062679	1.10506	1.622025
9	3.305695	0.233368	2.7436
10	3.866645	-2.28924	3.31497

3.1. Performance Evaluation of New Model

A numerical case was taken to evaluate the accuracy of the proposed model, in which the antenna height is constant and equal to 0.2 meters from the ground, the radial angle (θ), and the distance between the transmitter and receiver are 0 degrees, 5 meters respectively. Table 5 displays the neural network constants for input and output from Matlab Simulink, which are essential for normalizing the inputs and denormalizing the outputs.

Table 5.
The neural network constants for inputs and output.

Neural network constant			
	Inputs	Outputs	Inputs
	Radial angle (θ)	Distance (d)	Radial angle (θ)
Xoffset	0.01	5	0.01
Gain	0.005926102	0.057142857	0.005926102
Ymin	-1	-1	-1

3.2. Calculation Steps

1- Normalize the input data (x) using Eq. 9

$$Nx = \big((x - x.\text{xoffset}) * x.\text{gain}\big) + x.\text{ymin} \qquad (9)$$

So the normalize value of radial angle (Nθ) and distance are (-1) and -1 respectively.

2- Calculate Ei using 10 and Table 4, then calculate the activation function (Ai) from Eq. 6, as well as the results shown in Table 6.

$$E_i = w_{i1}d + w_{i2}\Theta + b_i \qquad (10)$$

Table 6.
The example resultes calculation values of EI and a.

Ei	Ai
4.607473	0.999800939
1.435252	0.892737849
-2.81511	-0.99285014
5.41231	0.999960194
-7.23837	-0.99999897
-0.18007	-0.1781446
-2.60481	-0.98913194
0.454282	0.425412101
-0.79566	-0.66160294
1.737332	0.939916403

3-Calculate the output (y) using Eq. (7)

y_i= -0.603247166

3- Denormalizing the output (y_i) using Eq. (8)

So the prediction value for path loss (PPL) for radial angle 0 degree and 5 meter distance is 92.7447; it's high and agrees with the empirical measured value (Table 5). The previous paragraphs provide the assumptions for the lognormal shading model Eq. (1), and its linear regression equation is: [25].

$$Y = 64.84 + 32.1\log(d) \qquad (11)$$

Here is another example of calculating path losses using the lognormal shading model Eq. (2), as well as the model proposed in this study for different values of radiation angle and the distance, Table 7:

Table 7.
Numerical example Resultes for various Raial angle and distance using proposed model and linear regression model.

Distance (m)	Radial angle (θ^o)	linear regression equation (dB) Eq.11	Our prediction model (dB)
15	22.5	102.59	104.79
5	45	87.27	90.38
20	67.5	106.60	106.77
30	90	112.25	114.48
10	112.5	96.94	97.12

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4. Results and Discussion

As seen in Figure 6, the proposed PL prediction model based on network weights works very well. Statistical values like R and MSE show that the proposed formula is excellent at describing all possible operating conditions. The average square error and linear correlation coefficient of the new proposed model are 0.688047782 and 0.9924, respectively.

For the same sender location (h), radial angle (θ), and distance (d), experimental data for path loss (PL) is compared with those calculated using new formula, the FSPL model, the Two-Ray model, and finding of Elmezughi, et al. [26] as shown in Table 8 and described in Figures 7-9. Clearly, the results of the new formula and the experimental data are perfectly compatible, and more accurate from the normal logarithmic model proposed by Faruk, et al. [17] as shown in Figure 9.

According to Table 9 and Figure 7, the average absolute deviation value (AAPD) Eq. (12) for the results of the proposed formula, log-normal shadowing model, FSPL model, and Two-Ray model associations for the full experimental data bands are 0.51%, 4.1%, 40.579%, and 28.79%, respectively.

$$AAPD = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{O_i - N_i}{O_i}\right| x100 \qquad (12)$$

Table 8.
The Path loss of concrete surfaces environments predicted by the proposed model, two-ray model log-normal shadowing model, and FSPL model in [Db].

Transmitter antenna setting	d (m)	PL empirical measurements (dB)	log-normal shadowing model [23] (dB)	FSPL model (dB)	2-Ray model (dB)	Our prediction model (dB)
Radial θ degree	5	93	87.25	54	55.88	92.74
	10	100	96.94	60.04	67.95	100.45
	15	106	102.59	63.56	75,002	106.26
	20	112	106.6	66.06	so	111.21
	25	115	109.71	68	83.87	115.18
	30	116	112.25	69.58	$7,043	117.52
	35	120	114.4	70.92	$9.72	119.27
	40	120	116.26	72.08	92.04	120.39

Table 9.
AAPD (%) for log-normal shadowing model, FSPL, two-ray, and the proposed models.

Transmitter antenna setting	d (m)	APPD (%)			
		log-normal shadowing model [23]	FSPL model	2-Ray model	Our prediction model
Radial θ degree	5	6.18	41.92	39.91	0.27
	10	3.06	39.95	32.04	0.45
	15	3.21	40.03	29.24	0.21
	20	20	4.81	41.01	28.57
	25	4.59	40.86	27.06	0.16
	30	3.22	40.01	24.96	1.31
	35	4.66	40.89	25.23	0.6
	40	3.11	39.93	23.29	0.33
Average AAPD %		4.11	40.58	28.79	0.51

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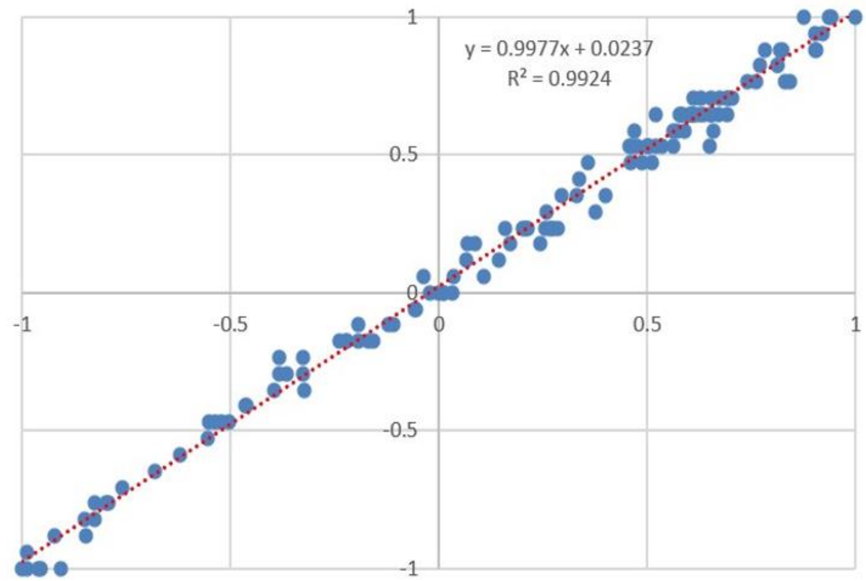

Figure 6.
Comparison of network output performance to experimental data.

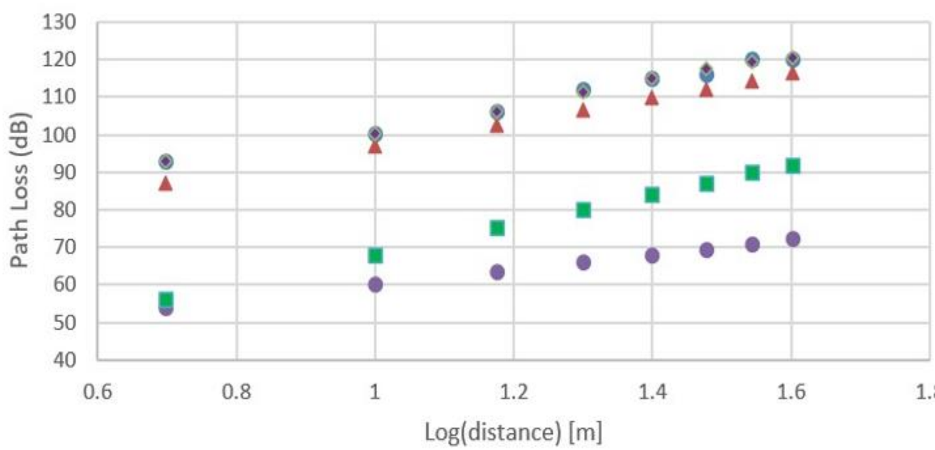

Figure 7.
A comparison of several models with proposed model outcomes for distance 5m and 0° radial angle.

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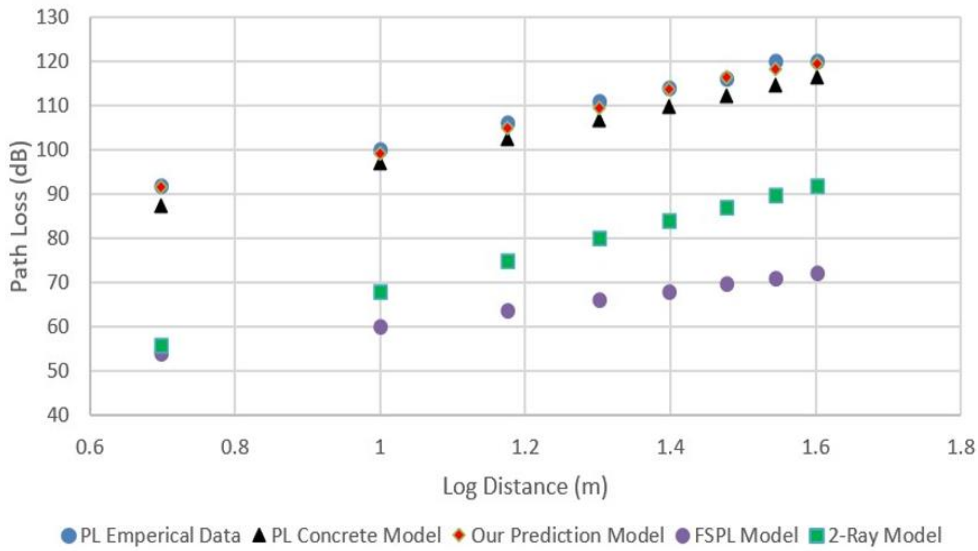

Figure 8.
A comparison of several models with proposed model outcomes for distance 10m and 0º radial angle.

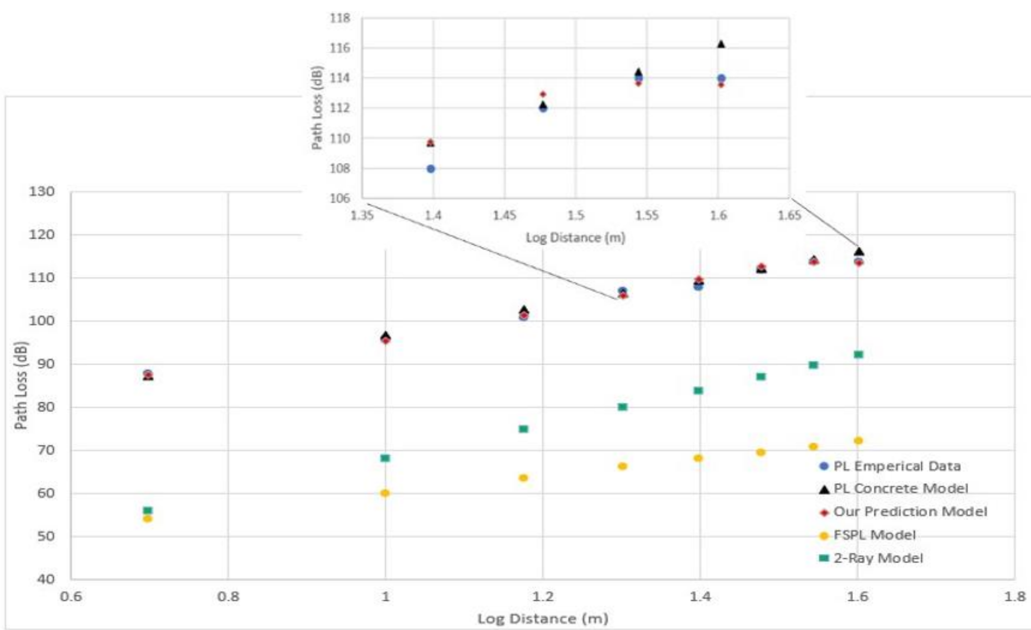

Figure 9.
A comparison of several models with proposed model outcomes for distance 40m and 0º radial angle.

In the end, Eq. (5) was used to determine the relative importance of each of the factors used. The total weights, known as *Imp (i)*, for input factors such as the radial angle of the receptor site and the distance between the transmitter antennas and the receiver were 1.40 and 2.49 respectively. This indicates that the distance between the transmitter antennas and the receiver has a stronger impact on path loss.

5. Conclusion

A methodology has been developed based on the use of ANN weights to calculate the path loss of wireless signals that spread in concrete surface environments. Using the gross quantitative weight formula, the user can get results without having to run the relevant ANN software. Also, the distance between transponder antennas has been shown to be the main factor affecting the amount of track loss in a concrete environment. The new formula for calculating path loss has a larger computability range and is more accurate than [26]. Finally, the new formula showed that it accurately outperformed the prediction of path losses when compared to the previous association log-normal shadowing model (given by Elmezughi, et al. [26]) and the Two-Ray and FSPL models.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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