ANN-Based Formulation of Path Loss Prediction for Radio Wave Propagation for Indoor Agriculture and Sensor Networks

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The wireless sensor network has proven to be a useful instrument for providing farmers with accurate data on the condition of their crops. Although the FSPL, 2-Ray, COST235, and linear path loss regression curve fit model (LRCFM) give an explanation for the propagation of 2.4 GHz radio waves through vegetation, several substantial inconsistencies were discovered when applied to field experiments with plants greenhouses. This study uses artificial neural networks (ANNs) to make a prediction model that can be used to look at how tree growth affects path loss across a wide range of transceiver heights and operating parameters. The artificial neural networks were created using the experimental data. The neural network is trained using as input parameters the height and distance of the antennas of the transmitting and receiving nodes and, as a desired parameter, the amount of path losses (PL). Using the network weights, a new PL prediction formula was created. This formula predicts the amount of path losses more accurately, and the mean absolute relative deviation (AAPD) between our formula and the FSPL+COST235, 2Ray+COST235, FSPL, 2Ray, and LRCFM correlations is 0.36%, 17%, 55.5%, 42.7%, 81.11%, and 5.454%, respectively.

Keywords: propagation model, deep learning, neural network, precision agriculture, Wireless sensor networks.

1. Introduction

The ZigBee protocol is one of the most promising WSN protocols. WSN has a wide application field starting with household, medical, industrial, and agricultural equipment.

ZigBee is cost-effective and energy efficient as it operates according to the IEEE 802.15.4 physical radio specification. There is a good chance that wireless network sensors could be used in agriculture by converted into smart greenhouses through the use of information technology and sensors, they can help boost agricultural productivity. (Andrianto, H. et al, 2020; Morais, R., et al. 2008)

Many of the greenhouse's test points are outfitted with wireless nodes outfitted with various sensors, such as those for soil moisture, fertilization, irrigation, ambient temperature, and humidity, which feed the readings of these sensors into the greenhouse's monitoring and control system. The gaps between nodes, the growth of vegetation, and the terrain, as well as the altitude at which the transmitter and receiver are installed, all have an impact on the quality of communication between sub-nodes and the main node.

The lack of precision in describing wireless networks necessitated a thorough investigation and analysis of the form of radio wave propagation in open and closed fields, as well as the use of a high-accuracy model for calculating wireless signal path losses. (Mestre, P., 2010)

Most of the published works use the free-space path loss (FSPL) model and the two-Ray path loss model to figure out how much a path loss is in a wireless sensor network. (Alexis Barrios-Ulloa, A. et al., 2022, Balachander, D. et al., 2013; AlSayyari, A. et al., 2014; Otero, C.E. et al., 2014)

The FSPL model implies that the transmitter and receiver communicate in direct line-of-sight (LOS) that is neither obstructed nor reflected. However, radio signals are often reflected by things that are in the path of the signal or close to it. The FSPL model provides a lower constraint on the route loss estimate, as given in Eq. (1): (Mao, G. et al. 2007)

$$\mathrm{PL_{FSPL}} = -27.56 + 20\log(\mathrm{df}) \qquad (1)$$

the distance d in meters between the transmitter and the receiver, and the frequency f in megahertz (MHz) of the wave.

The 2-Ray model depicts a direct wave from the transmitter and a reflected wave from the earth's surface both making their way to the receiver. In the 2-Ray model, the ground is assumed to be flat, and the height of the antennas that transmit and receive the signal is much less than the distance between them. (Rappaport, T.S., 2002)

Path loss may be calculated using the Plane Earth (PE) model rather than the FSPL model. This model incorporates the ground beam and LOS beam reflection effects provided by Eq. (2):

$$\mathrm{PL_{PE}(dB)} = -20\log(\mathrm{h_T h_R}) + 40\log(\mathrm{d}) \qquad (2)$$

where d is the sender-to-receiver distance in meters and h_T and h_R are the respective heights in meters of the transmitter and reception antennas.

Many empirical route loss models for different ways that WSNs can be set up in the real world have been put forward. Meng et al. (2009) describe a path loss model for how radio waves move through tropical forests. Balachander et al. (2013) used path loss measurements taken in farms and gardens to characterize experimental models. Correa et al. (2013) describe an experimental model that can be used as a guide for putting WSNs in vineyards. Al-Sayari et al. (2014a, b, c, d), the authors gave four route loss models for WSNs that are used in places with sandy terrain, dense trees, concrete surfaces, and artificial turf.

Otero et al. (2014) also showed radio frequency measurements and an experimental pathway loss model for wireless sensor networks in environments with tall grass. Raheemah A.

(2016) made a unique linear path loss regression curve-fitting model (LRCFM) based on the regression method to figure out the overall path loss within the greenhouse.

Cama-Pinto D. et al. (2023) suggest a method that uses machine learning to build an real time model of how radio waves weaken as they pass through vegetation. This model takes into account the height and distance between the WSN nodes' transceivers.

On the other hand, discovered an article investigated how much attenuation trees create in wireless signal transmission (Li, P., et al. 2014), Another study looked at how the path loss model improved WSNs installed in mango greenhouses (Auda Raheemah, et al. 2016), Another study investigated the frequency of WSNs in tomato greenhouses for monitoring environmental factors as well as precision agriculture (Cama-Pinto, et al. 2019; Cama-Pinto, D. et al. 2020). Nevertheless, none of the data studied could be utilized to create RF propagation models based on the greenhouse prediction model, which is what this study performed. To figure out the accuracy of the new formula, its results were compared to a number of leaf model correlations, as shown in the paragraphs that follow.

2. Total Path loss Models

The overall path loss may be broken down into three parts: path loss due to wave extension, free space path loss, and obstacle path loss within the broadcast path, as shown in Eq. (3), where PL_T denotes total path loss, $PL_{f\ s}$ denotes free space path loss, and PL_v denotes obstacle path loss.

$$PL_T = PL_{fs} + PL_v \qquad (3)$$

The density of tree leaves causes an increase in signal power losses. Researchers have now established methods to include these considerations via the implementation of empirical foliage modeling employ different leaf designs and operating frequencies to compute the additional loss. (Rappaport, Theodore S., 1996; Seybold, John S., 2005; COST 235, 1996; Al-Nuaimi M.O.; Stephens R.B.L., 1998)

The modified Weissberger's exponential decay model, It is relevant if there are heavy trees in the way of the waves and is given by Eq. (4), is one of the most notable empirical models.

$$PL_w(dB) = 0.45 \times f^{0.284} \times d \qquad m \leq d < 14m \qquad (4)$$

where f is the wave's frequency in MHz and d is the distance between the sender and receiver in meters. (Seybold John S., 2005)

The COST 235 model was introduced based on measurements taken at millimeter-wave frequencies throughout a small forest. Eq. (5) illustrates this:

$$PL_{COST235}(dB) = \frac{15.6d^{0.26}}{f^{0.009}} \qquad (5)$$

The COST 235 model was used in order to quantify the effect of trees in two different seasons, both with and without leaves. On COST 235 models, f is the wave's frequency in MHz and d is the distance between the sender and receiver in meters.

Different experiments were done with different transceiver heights to find out what effect tree density has on path loss. To calculate the overall path loss in a greenhouse, a novel linear path loss regression curve-fitting model (LRCFM) Eq. (6) was developed using the regression approach. (Raheemah Auda, et al. 2016)

$$PL_{LRCFM} = 71 + 27\log(d) \qquad (6)$$

Neural networks are excellent instruments for approximating nonlinear functions, and they are employed in a multitude of fields. Artificial neural networks are made up of tiny, linked processing units. Along the interconnection, data is transferred between these components. They discover the connection between inputs and outputs. An input, hidden, and, output layers are typical components of a network. (Mousavi Dehghani, et al. 2008, Alrubaie, Hiba, et al. 2023)

The connection weight multiplies each entry. In the most basic scenario, biases and products are simply combined together before being transformed into a result and then an output using a transformation function. (Sözen, A., et al. 2005)

The training phase of a neural network is crucial. Backpropagation is the most well-known training algorithm. Backpropagation neural networks have inputs and outputs, and in most applications, they have a single hidden layer. Backpropagation of gradient descent training methods is frequently too slow for real-world issues. Standard numerical optimization techniques are used in algorithms that are faster, such as Levenberg-Marquardt (LM), Quasi-Newtonian (QN), and Conjugate Gradient (CG). (Sözen, A., et al. 2009)

The mean squared error (MSE) is a measure of learning error that is defined as follows:

$$MSE = \frac{\sum_{i=1}^{m}(DO_i - NT_i)^2}{m} \qquad (7)$$

Where DO_i is the desired output of the training data, NT_i is the network output of the training data, and m represents the quantity of data in the training dataset. (Gevrey, M., et al. 2003)

Olden J. D. et al. (2004) investigated many methods for determining the importance of parameters in artificial neural networks using a simulation-based methodology. When it comes to identifying the relative relevance of parameters in artificial neural networks, the proposed connection weight strategy performs better than any previous approach. The connection weight technique combines the output of the hidden neuron's connection weight to the output neuron and the output of the input neuron's connection weight to the hidden neuron for all input parameters. When a parameter's connection weights add up to a large number, it becomes significant.

3. ANN DETAILS AND DATA PREPARATION

Artificial neural networks were employed in this study to forecast the amount of path loss in a wireless sensor network. To train the network, experimental data was extracted from the several paper (Raheemah A. etal. 2016, Cama-Pinto D. et al. 2019), where the input vectors of the network were the ground elevations of the transmitting and receiving nodes from the ground and the distance between them, and the output vector was the amount of path losses.

Table 1 summarizes these data ranges. Fig. (1) depicts the ANNs' design. During the tests conducted within the greenhouse, the height of the transceiver's omnidirectional antennas was (50, 100, 150, 200, 250, and 300) cm from the ground. Fig. (2) shows the minimum and maximum ranges measured when the antenna heights of the transmitting and receiving nodes were 0.5 m and 1.5 m, respectively.

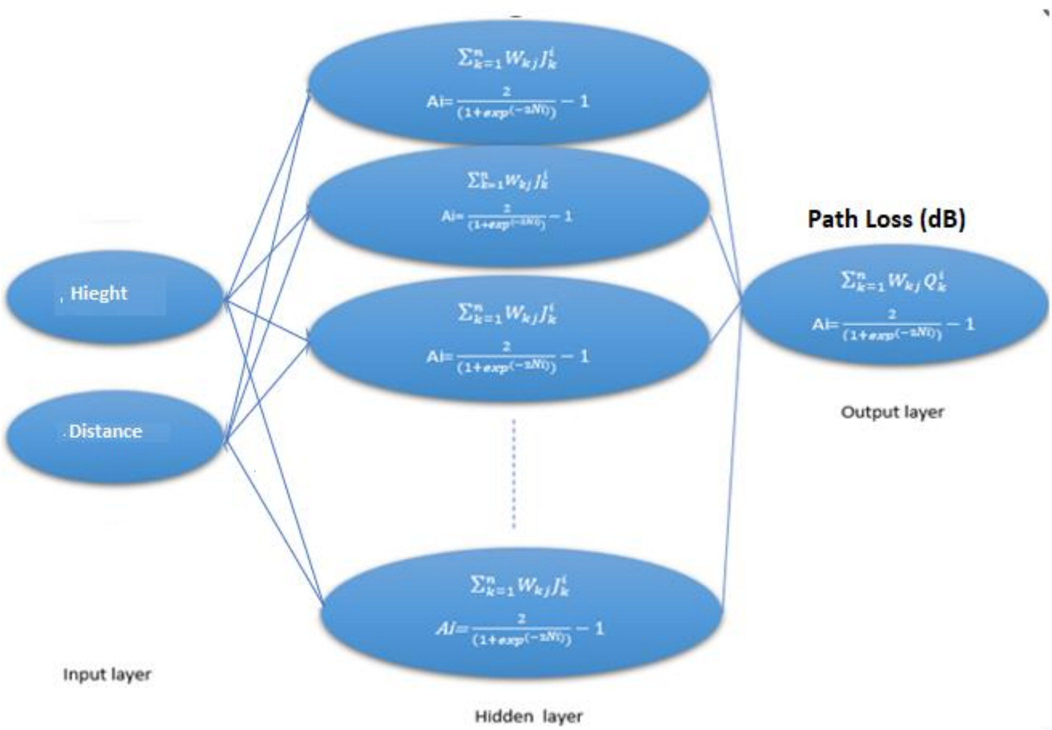

Fig.1. The proposed architecture of ANNs.

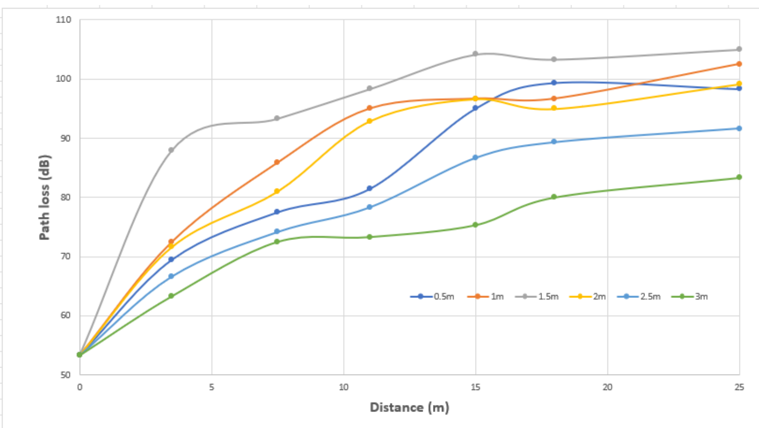

Fig.2. depicts the maximum coverage and signal strength between a transmitting and receiving node at various distances above ground.

Table 1: The experimental data ranges that were utilized to train the network. (Raheemah A. etal. 2016, Cama-Pinto D. et al. 2019)

	PL (dB)					
H(m) / D (m)	0.5	1	1.5	2	2.5	3
0	53.33	53.33	53.33	53.33	53.33	53.33
3.5	69.5	72.5	87.98	71.65	66.66	63.33
7.5	77.5	85.83	93.316	81	74.16	72.5
11	81.454	94.98	98.314	92.9	78.32	73.32
15	94.982	96.648	104.145	96.638	86.652	75.32
18	99.347	96.648	103.312	94.982	89.318	79.988
25	98.314	102.479	104.978	99.147	91.65	83.3

The ANN has three layers and uses backpropagation to learn from the data it is given. In this study, The LM learning algorithm was used since it is more efficient and faster than other algorithms. The Pureline and Tan-Sigmoid functions were used for the input and output of the hidden layer, respectively. The MATLAB software was used to create a computer program (Matlab User's Handbook, 2020a)). During training, a hidden layer of ten neurons was employed to improve accuracy. The hidden layer's neurons have two responsibilities: adding up the weighted inputs they receive and passing that total on to either the output neurons or additional neurons in the same hidden layer through a nonlinear activation function. Normalizing the distribution data enhances the correlation coefficient between the dependent and independent factors. The inputs and outputs of Eq. (8) are normalized to the interval [-1,1].

$$\mathrm{X_{nor}} = 2 \times \left(\frac{\mathrm{X_{OD}} - \mathrm{X_{minmum}}}{\mathrm{X_{maximum}} - \mathrm{X_{minimum}}}\right) - 1 \qquad (8)$$

where X_{OD} stands for the starting data, $X_{minimum}$ for its lowest value, $X_{maximum}$ for its highest value, and X_{nor} for the normalized output. The input and goal data were normalized before being utilized to train the network. The ANN can be trained without any extra patterns. ANNs may accurately anticipate the acquired values using statistical metrics like the mean squared error (MSE) and the linear correlation coefficient (R) if they are trained with enough data. After a successful training session, the network was put to the test with real-world data.

4. RESULTS and DISCUSSION

The ANNs in this work were designed using a collection of 42 experimental data points for path loss. Moreover, 30 records were used for training, 6 for validation, and 6 for testing.

The LM technique with 10 neurons in the hidden layer performed the best with the fewest errors.

In terms of Minimum Absolute Error (MinAE), Normalized Mean Square Error (NMSE), Maximum Absolute Error (MaxAE), Mean Square Error (MSE), Mean Absolute Error (MAE), and the linear correlation coefficient (R) between the experimental data and the output, Tables 2 and 3 assess the performance of the ANN for two cases: first, both transmitting and receiving nodes' antennas are placed at 0.5 (scenario 0.5m), while in the second case they are placed at 1.5 meters above the ground (scenario 1.5m).

Table 2: The findings of the ANN model on the 0.5meter test dataset.

Performance parameters	The network evaluation
MinAE	0.003523289
MaxAE	2.056589119
MSE	0.759659771
MAE	0.644812121
R	0.9972
NMSE	0.00162

Table 3: The findings of the ANN model on the 1.5 m test data set.

Performance parameters	The network evaluation
MinAE	0.006284176
MaxAE	3.07346844
MSE	0.48245806
MAE	0.229288274
R	0.9987
NMSE	0.00135

Because the error characteristics of the test and validation sets are similar, the results appear acceptable given the small amount of network data, and no severe overfitting appears to have happened. The path loss prediction model will be taken from Scenario 1.5m, since it has the least path loss. The fixing of both the transmitting energy and the height of the nodes, the path loss of the wireless network in the greenhouse depends on how far apart the sending and receiving nodes are from one another. With the aforementioned network training, the algorithm's weights were used to come up with a formula for predicting Wireless network path loss. Eq. (9) gives the Tansig as activation function utilized in the hidden layer:

$$A_i = \frac{2}{(1+\exp^{-2M_i})} - 1\,, \quad i = 1:10 \qquad (9)$$

The values of Mi are listed in Table 4. As a result, Eq. (9) and Eq. (10) allow for the prediction of wireless network path loss.

$$PL_{1.5m} = 0.099995A_1 - 0.23268A_2 - 0.24114A_3 - 0.25616A_4 + 1.19406A_5 - 0.06549588A_6 - 0.3265009A_7 - 0.154316A_8 + 0.2729222A_9 + 0.698229379A_{10} - 0.00454 \quad (10)$$

Table 4: Scenario 1.5m, weight values calculated by the Levenberg-Marquardt algorithm with 10 neurons.

$M_i = W_{i1} x D + W_{i2} x h + b_i$			
i	W_{i1}	W_{i2}	b_i
1	-0.92024	4.535022	4.156035
2	4.438692	-0.84711	-3.34391
3	-1.82848	4.257503	1.978151
4	4.482065	-1.21699	-1.77728
5	1.30909	-0.24369	-0.41696
6	2.392758	-3.70449	-0.00617
7	4.937716	-2.34521	0.700464
8	-2.4965	4.11114	-1.94444
9	0.230107	8.668886	0.805272
10	9.057415	0.875293	6.948328

Fig. (6) depicts the results of the $PL_{1.5m}$ prediction formula based on the algorithm's weights. Statistical measures such as R and MSE show that this formula gives an accurate estimate of path losses over a wide range of inter-distances between transmitting and receiving nodes. Under the new suggested model, the mean squared error is 0.48245806, while the linear correlation coefficient is 0.9987. In Fig. (7), the experimental data for path losses ($PL_{Exp.}$) are compared to those calculated by the new formula ($PL_{1.5m}$), FSPL, 2Ray, LRCFM, FSPL + COST235, and 2 Ray + COST235 for the same distance and height at which the transmitting and receiving nodes are installed. It can be seen that the findings of the $PL_{1.5m}$ model and the experimental data match up very well. According to Fig. (7), the Average Absolute Percent Deviation (AAPD) (Eq.11) parameter for $PL_{1.5m}$ model, FSPL+COST235, 2Ray+COST235, FSPL, 2Ray, and LRCFM correlations is 0.36%, 17%, 55.5%, 42.7%, 81.11%, and 5.454% respectively. The findings of the $PL_{1.5m}$ model and the experimental data coincide quite well, as seen in Fig. (3-5).

$$AAPD = \frac{1}{N}\sum_{i=1}^{N} \left| \left(\frac{PL_{exp} - PL_{cal}}{PL_{exp}}\right) \right| \times 100 \quad (11)$$

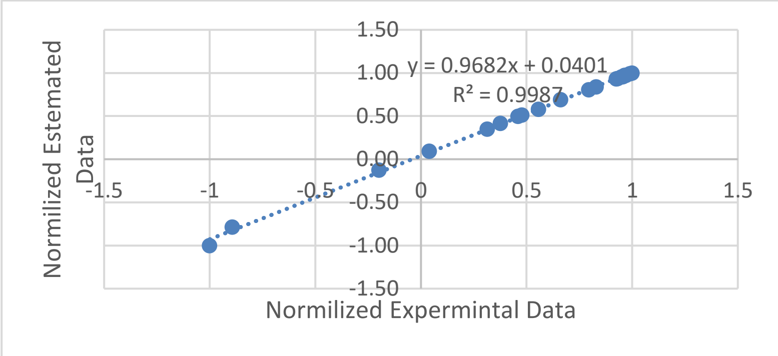

Fig.3. Comparison of network output performance to experimental data.

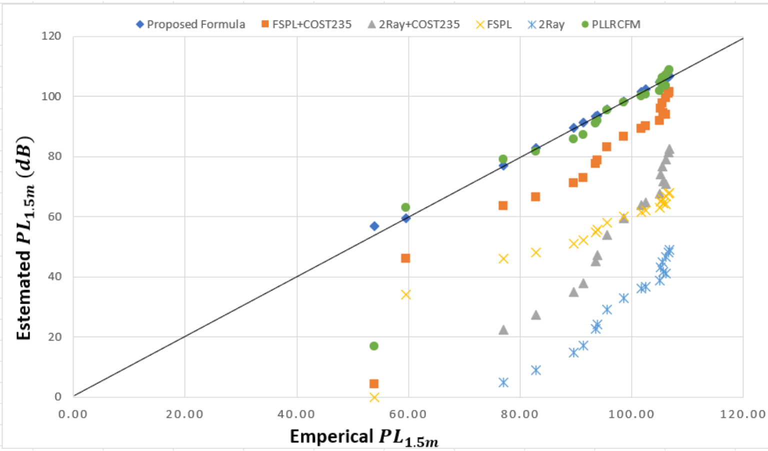

Fig.4. A comparison of several models (FSPL+ COST235, 2Ray + COST235, LRCFM) with proposed formula outcomes.

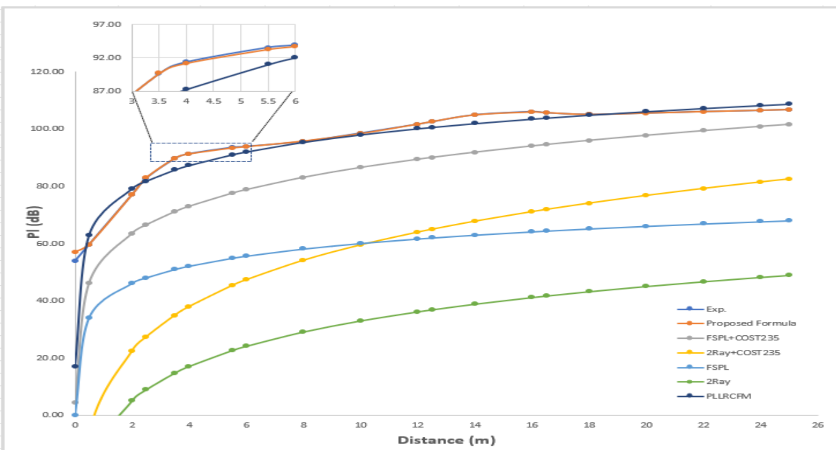

Fig. 5. Compares the new prediction model's accuracy to several commonly used path loss models.

5. Conclusions

Path losses in greenhouse wireless networks were quantified using an ANN-based technique, and an updated formula for estimating these losses as a function of height and distance was introduced. The developed formula enables the researchers to apply the model without resorting to a computer with ANN software installed. Through predicting the amount of received signal power lost, the suggested formula proved to be more accurate when compared to standard models for path loss estimation.

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