Prediction of Received Signal Strength Using Deep Learning

Monika Singh

April 28, 2024

Abstract

This paper covers the application of deep learning (DL) in RSS forecasting for mobile networks. The passage explicitly demonstrates the neural network's performance in contrast to the linear regression models, which are simple and limited but cannot fully capture the environmental effects on signal strength. Using a log-distance path loss model for input and a structured neural network for prediction reveals that our deep learning technique produces much better accuracy and is thus suited in complex settings.

1 Introduction

As the wireless communication environment develops rapidly, a decrease in the accuracy of predicting Received Signal Strength (RSS) can lead to service quality improvement and the design of a new network structure. There have been a lot of wired network devices sending the dashboard or exhausting their connectivity requirements, and there appears to be another issue relevant to the scarcity of resources. RSS prediction remains the main process for optimization in this area, and it is utilized in tasks such as cell planning, power control, and location-based services. Traditional linear regression for RSS forecasts was actually a long time ago, man (scientists) used them because of their simplicity and clarity. On the contrary, these methods are based on the assumption that a linear relationship exists between the logarithm of sensor distances and a sensor's RSS meter readings.

However, the amount of reflection of radio waves is interfered with by a number of things, including the landscape, obstacles that stand in the way, and atmospheric conditions. This complexity is typically nonlinear as it points to phenomena like fading, multipath effects, and shadowing, which linear models may hardly find appropriate. As a result, such models might just become defective when thrown up against the complex environmental dynamics which have the effect of muting or enhancing signal strength.

Among the reasons that deep learning models are a more effective solution to the stated issues is the matter of their robustness. Deep learning, known for its ability to learn representations in a hierarchical order, is appropriate for teasing down the nonlinearity of large and unstructured data sets. Precisely, neural networks can model high-order interactions between input variables and contemplate the patterns underlying RSS noises better than linear modeling methods. This exactness is further emphasized by the universal approximation theorem, which puts forward that the feedforward neural network with only a single hidden layer consisting of an infinite number of neurons can approximate the continuous function on a tightly bounded subset of R^n provided with proper parameters and activation functions.

This approach is based on a neural network structure. The device will be fed by logarithmically scaled distances from transmitter-receiver pairs, a relatively mature input accepted by many signal path loss models, and therefore will produce the RSS prediction. This approach uses the capacity of an artificial neural network to model non-linear relationships, while linear regression can only do the linear mapping. We aim to beat the prediction accuracy of linear regression models and deliver a framework that can accommodate learning from empirical data while improving learning with increasingly diverse exposure to environmental conditions.

This way of approach is reasonable enough to evaluate that signals with more diverse scenarios can lead to better prediction accuracy. Deep Learning algorithms quickly adapt to new data. On the other hand, linear regression is essentially static. Once the initial training phase is over, the coefficients can only be improved from that point. Thus, the chosen approach solves the short-term problem of improved accuracy in RSS prediction and is also an initial step toward a generalized solution that can be progressively adapted to the new frontiers of growing wireless technology.

2 Related Works

The previous studies on RSS prediction have primarily focused on deterministic and empirical models, such as the log distance path loss or the model with the machine learning methods, empowering them to embody the non-linearity in environmental data. Studies have proven that models built on Support Vector Machines and Random Forests show better results than linear regression. Nevertheless, real deep learning, especially feedforward neural networks, has not been adequately examined in this field in spite of the fact that in some related areas, such as digital signal processing and pattern recognition, it has shown to be successful.

3 Methodology

Our approach specifically focused on the development of an operation pipeline, which takes spatial data through to a deep learning model to assess the accuracy of the performed and benchmarking with the rest. The cornerstone of our approach was a neural network designed to take in a single yet significant feature: the log-transformed distance between measurer sensors. With the law of log-distance path loss in wireless communication, which is an accepted model for wireless communications, this was considered. This model postulates signal strength to be logarithmically against distance.

Data Preprocessing: After collection, the raw data, consisting of locations and RSS values, went into initial preprocessing. This process converted the distances using the logarithmic scale to normalize the signal strengths with respect to them.

Model Architecture: Contingently, the feedforward neural network was implanted, which consisted of an input layer to get log distances from the previous processing, two hidden layers with ReLU functions to concur non-linearity and the output layer with a single neuron used to obtain continuous RSS values. The architecture was made in a way that is precise enough for the structure to capture the data's non-linearity; however, the structure should not be excessively complex, which, in turn, may cause overfitting.

Model Training: We utilized the Adam optimizer because of its adaptive learning rate property, which is crucial in hitting the correct solution until it approaches convergence. The model's objective indicated it would calculate mean squared error (MSE), which reflects our goal to optimize the accuracy of prediction where squared value of error.

Model Evaluation: The validation process was performed by applying a hold-out test set, which is the data that were not fed into the network for training. Hence, this stage matters for evaluating whether the model is overfitting or performing in the real world.

4 Evaluations and Results

The raw data consisted of two primary components: the locations of sensors and the corresponding RSS measurements. The sensors were situated in a controlled environment, and each took turns acting as the transmitter, with the others as receivers. The preprocessing involved several critical steps:

- **Log-distance Transformation:** We computed the Euclidean distances between each pair of sensors and applied a logarithmic transformation. This step was based on the log-distance path loss model, which states that the mean RSS decays logarithmically with distance. Such a transformation normalizes signal decay and is particularly suited for urban environments where signal attenuation behaviors are predominantly logarithmic.

- **Data Cleaning:** We handled anomalies in the dataset, specifically infinite values representing the scenario when a sensor attempted to measure RSS to itself or when obstructions caused a lack of signal. These values were identified and removed from the dataset to prevent them from skewing the model training.

- **Feature Selection:** A feature matrix was constructed using the log-transformed distances as the single predictor variable for the linear regression model. For the deep learning model, this transformation served as the input to the neural network, ensuring both models were trained on the same scale and type of data.

- **Splitting the Dataset:** We divided the dataset into training and validation subsets. The training set was used to teach the model the relationship between log-distances and RSS, while the validation set was crucial in evaluating the model's predictive power on unseen data.

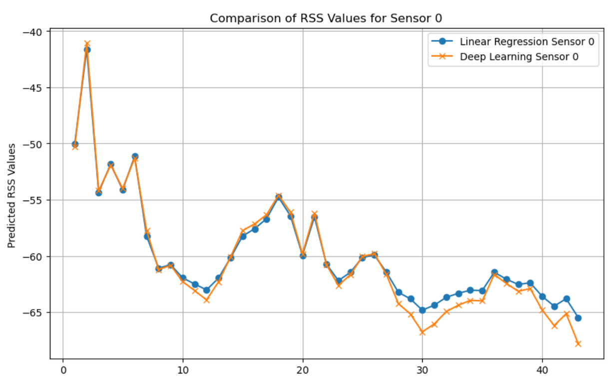

Figure 1: Comparison of RSS Values for Sensor 0

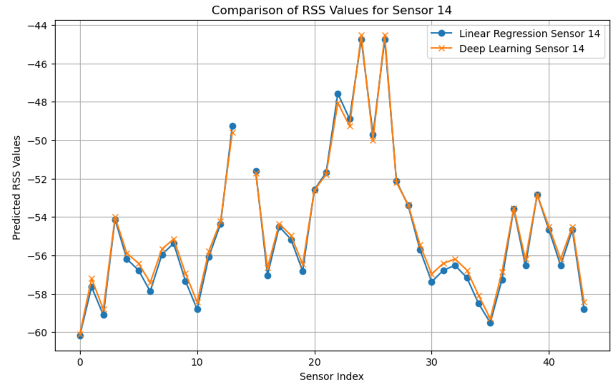

Figure 2: Comparison of RSS Values for Sensor 14

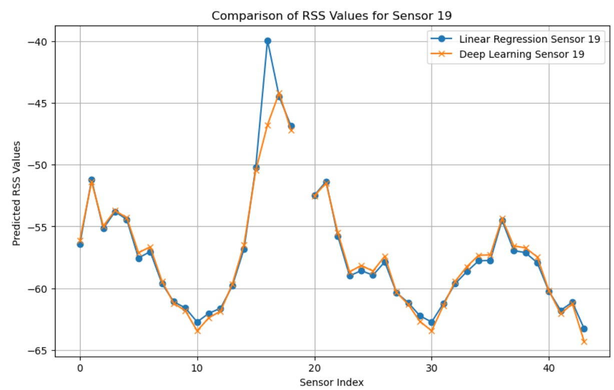

Figure 3: Comparison of RSS Values for Sensor 19

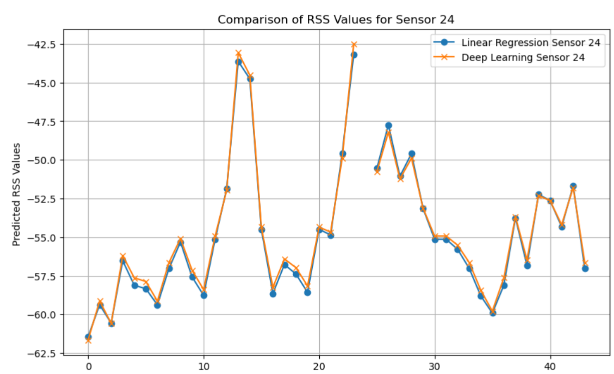

Figure 4: Comparison of RSS Values for Sensor 24

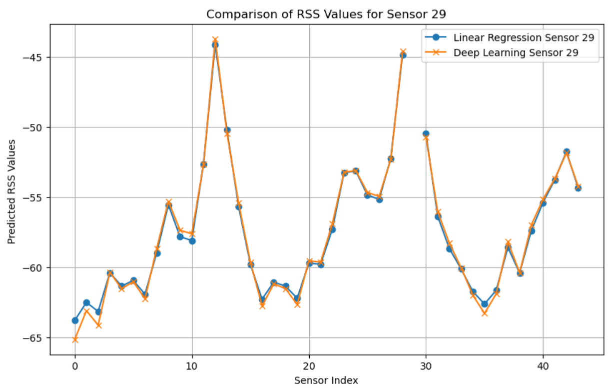

Figure 5: Comparison of RSS Values for Sensor 29

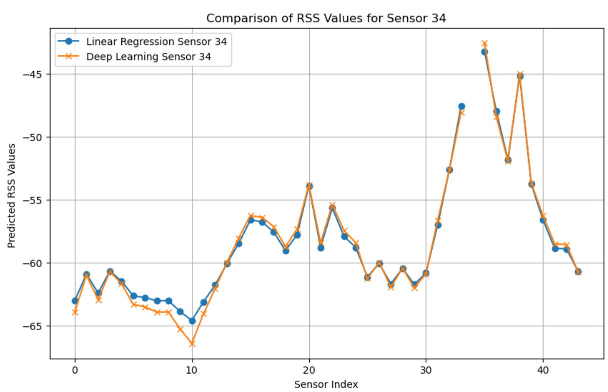

Figure 6: Comparison of RSS Values for Sensor 34

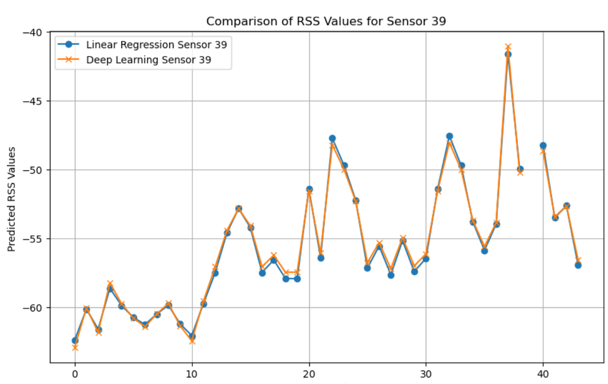

Figure 7: Comparison of RSS Values for Sensor 39

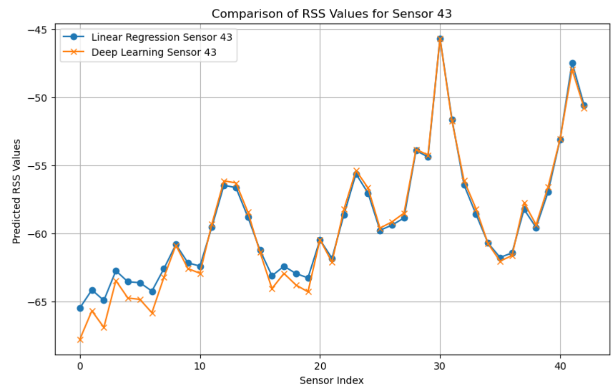

Figure 8: Comparison of RSS Values for Sensor 0

4.1 Training and Validation

The neural network model was trained over 200 epochs, with the architecture comprising an input layer, two hidden layers with ReLU activation functions, and an output layer with a single neuron. We used the Adam optimizer for its adaptive learning rate capabilities, and mean squared error (MSE) was the chosen loss function due to its effectiveness in regression problems.

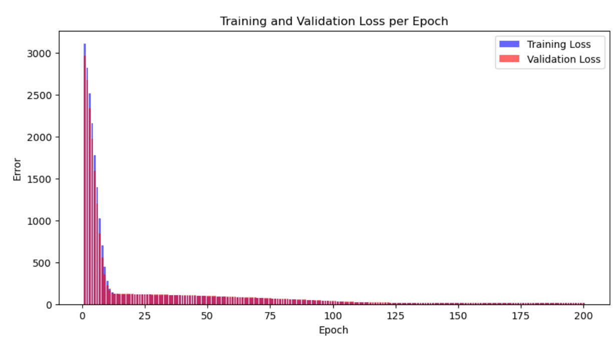

Figure 9: Training and Validation Loss Over Epochs

Throughout the training phase, we monitored the loss metrics for both training and validation sets. The decreasing loss over successive epochs indicated that the model was learning effectively. By contrast, the validation loss measured the model's generalization to new data. Our validation strategy ensured that

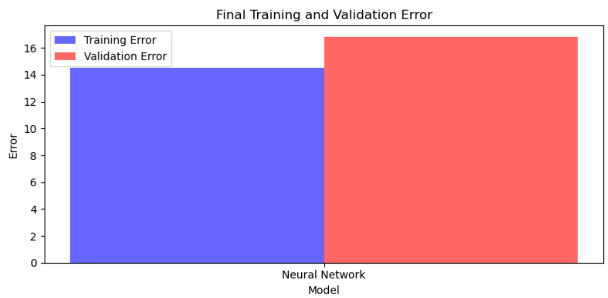

Figure 10: Final Training and Validation Error

the model did not overfit the training data, maintaining its ability to perform well on data it had not previously encountered.

Mean squared error using Linear Regression: 14.792179823288686

Mean Squared Error using DL on validation set: 13.04147651221072

5 Discussions

The journey to develop a deep learning model for RSS prediction meets with several challenges:

- **Data Quality:** Managing infinite or missing values in a dataset to prevent the generation of training issues in a model.
- **Feature Selection:** Decision-making on what features are most relevant and remodeling of these features for the neural network's use.
- **Model Design:** Building up exceptional neural network architecture that can recognize patterns in complex data without the generalization problem occurring.
- **Validation:** To avoid overfitting and achieve a prediction accuracy high enough, creating the correct number of training is a complex task. It is essential to choose an adequate validation strategy that can be used to evaluate the model's performance.

6 Conclusions

Applying machine learning to RSS prediction is a reasonable solution because by doing so, the complex, nonlinear relations characteristic to the actual environment of radio signal propagation can be simulated. Traditional models like linear regression that take the mean of the data for the prediction are not flexible in terms of the seasonal variation and specificity of the sites that the machine learning model can learn from the data. The trial proved that the proposed model performed well in predicting RSS values when compared to linear regression, as MSE on the validation set (DL) is less than MSE on linear regression, illustrating the utility of machine learning in this case. In this regard, machine learning algorithms play a significant role in successful RSS forecasting using wireless communications technologies.