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AI-Driven Optimization and Performance Analysis of LoRaWAN Network Deployment in Campus Non-Line-of-Sight (NLOS) Environment

Lubna Nazihah Md Lajis[1], Siti Zarina Mohd Muji[1]*, Fauziahanim Che Seman[1], Ariffuddin Joret[1]

[1] *Faculty of Electrical and Electronic Engineering*
Universiti Tun Hussein Onn Malaysia, Batu Pahat, Johor, 86400 MALAYSIA

*Corresponding Author: szarina@uthm.edu.my
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Abstract

LoRaWAN is widely used in low-power wide-area network (LPWAN) applications. However, network planning in a campus environment is challenging because of non-line-of-sight (NLOS) conditions due to buildings and obstacles. Conventional propagation models are not always capable of modeling the irregular behavior of wireless signals in such environments. In this research, the LoRaWAN signal performance in NLOS scenarios is predicted using a machine learning based approach. Field measurement data were collected by drive testing in a university campus. K-Nearest Neighbors (KNN) and Random Forest (RF) algorithms used to predict received signal strength indicator (RSSI) and signal to noise ratio (SNR). The results demonstrate the ability of the machine learning models to successfully learn real world signal variations in NLOS conditions. This approach offers a more practical way to enhance LoRaWAN network planning and deployment in campus environments.

1. Introduction

LoRaWAN is a popular low-power wide-area networking technology which provides long-range communication at low energy, making it ideal for large scale Internet of Things (IoT) deployments [1], [2]. In campus environments, signal propagation is heavily influenced by buildings, varried terrain, and infrastructure, leading to frequent non-line-of-sight (NLOS) conditions. Conventional network planning methods cannot capture the actual signal behavior in such complex environments and thus fail to provide reliable coverage estimation [3], [4]. To overcome this limitation, machine learning techniques have been increasingly applied to model wireless signal performance directly from measured data [5]-[7]. In this study, a data-driven LoRaWAN signal prediction model based on K-Nearest Neighbors (KNN) algorithm is developed to estimate received signal strength indicator (RSSI) and signal to noise ratio (SNR) in campus NLOS environment. Random Forest is used to help the feature analysis and robustness of the input parameter selection. The results show that the proposed KNN-based approach can be used to capture the real-world signal variations in NLOS conditions, which can be used for practical implementation of LoRaWAN network planning for-campus deployments.

2. Methodology

Field measurements were collected through LoRaWAN drive testing conducted within a university campus environment. The collected data set contains received signal strength indicator (RSSI), signal-to-noise ratio (SNR), geographical coordinates, and distance between end node and gateway. Data collection concentrated on the campus areas with building obstructions and low direct visibility which corresponds to non-line-of-sight (NLOS) propagation. A total of 490 data points have been collected throughout the entire UTHM campus and used to train the ML model. The overall workflow of the AI-driven LoRaWAN network optimization, including data collection, preprocessing, and model development, is illustrated in Fig. 1.

In this work, a machine learning model was developed to predict LoRaWAN signal performance. Rather than relying on explicit propagation equations, the model learns signal behavior directly from measured data. Spatial and distance-related parameters derived from GPS coordinates were used as input features, and the K-Nearest Neighbors approach considers nearby points to predict RSSI and SNR values as targets. The LoRaWAN-based IoT network architecture and AI-driven monitoring system used for data acquisition and model integration are shown in Fig. 2. This data-driven approach enables the model to reflect the real-world variation in signal that is present in complex environments [6].

A Random Forest regression model has been chosen because of its robustness, resistance to overfitting and high ability to model nonlinear relationships between input features and the signal performance. Before the dataset is used for training, it is divided into training and testing sets to evaluate the model's performance on unseen data. An 80/20 train-test split is applied, where 80% of the data is used for training and the remaining 20% is reserved for testing. The model was trained by using measured data in the field and tested on unseen samples as to determine its ability to generalize under NLOS [8]. The complete procedure of the machine learning model for prediction workflow is summarized in Fig. 3.

NLOS scenarios were determined by analyzing the layout of the campus, where the buildings and the surrounding structures interfere with the direct propagation path from the LoRaWAN gateway to the end node. These conditions cause extra attenuation, shadowing and multipath effects and so signal prediction is much more difficult than in line-of-sight (LOS) environments [4]. The Library Parking Zone in the UTHM Campus is used as an example of a NLOS area with buildings and obstacles.

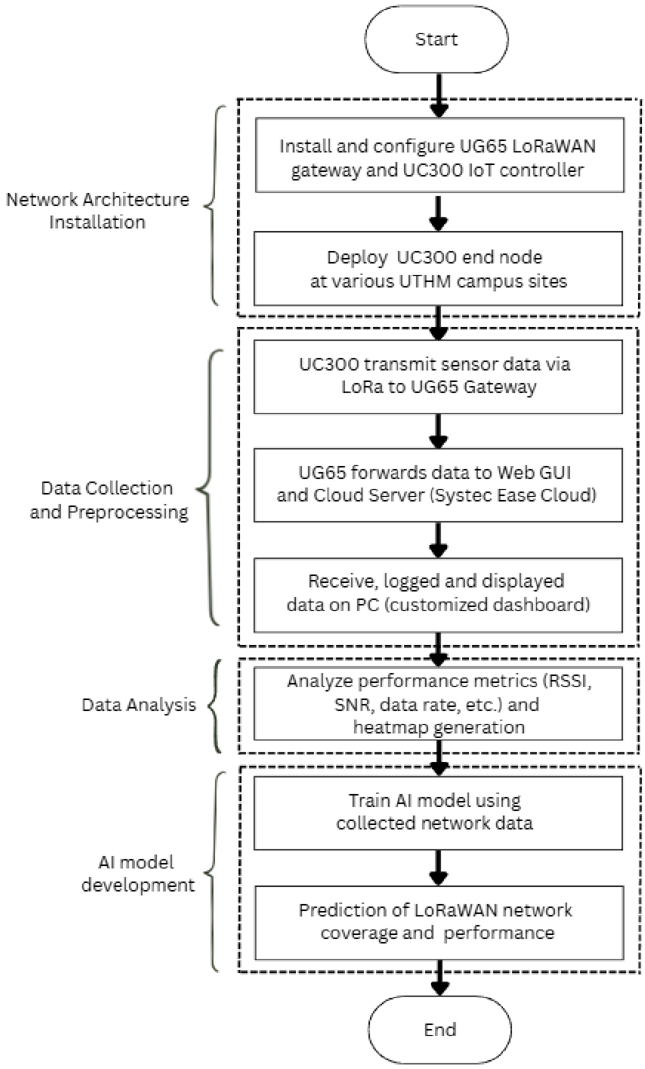


Fig. 1 *Flowchart of the AI-Driven Optimization Workflow for LoRaWAN Network Deployment*

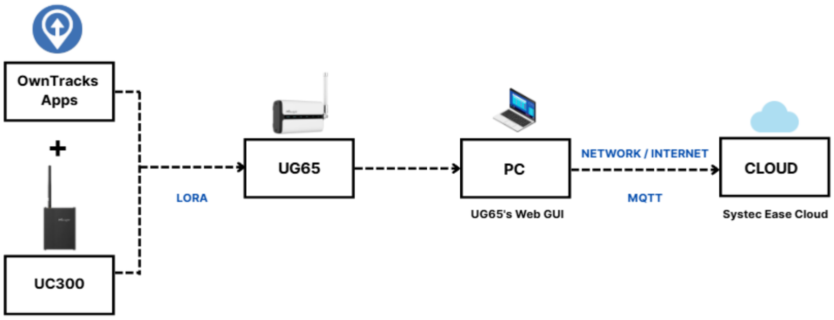


Fig. 2 *LoRaWAN-Based IoT Network Architecture with AI-Driven Monitoring System*

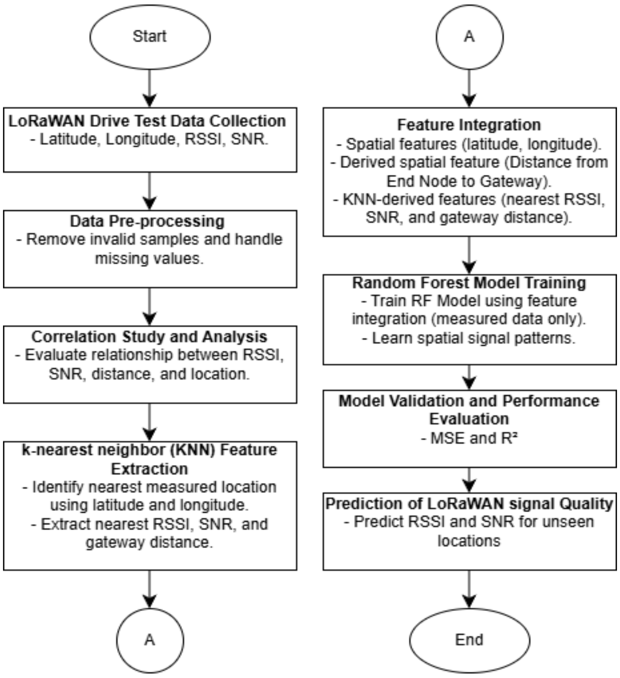


Fig. 3 *Overall Procedure Flowchart of Machine Learning Model*

2.1 Hardware Setup and Cloud Configuration

The LoRaWAN network architecture was deployed using a Milesight UG65 gateway installed on the 7th floor of the FKEE block. The gateway was centrally located and elevated to maximize its coverage, while the UC300 end node were moved across UTHM campus. Moreover, end node was configured with unique IDs and transmission settings to establish reliable communication with the gateway using the Milesight Toolbox software. Location data from the end node was obtained using the OwnTracks App, while the IoT MQTT Panel App was configured on a mobile phone to publish the location data. The gateway was connected to Systec Ease Cloud via Internet, where all the measurements were monitored and stored. The gateway was configured using its built-in web GUI for easy setup and management. Fig. 4 shows the process of testing and verifying communication between the end node and the gateway. This communication setup delivers a robust and scalable network for monitoring the performance of the LoRaWAN across the campus.

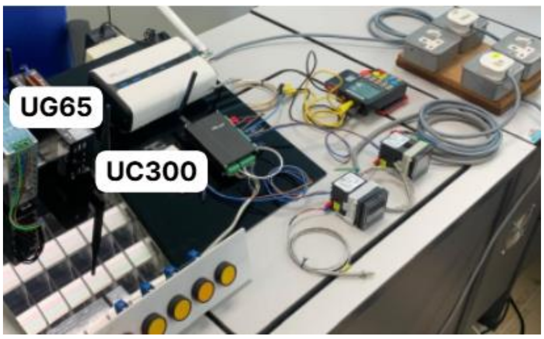
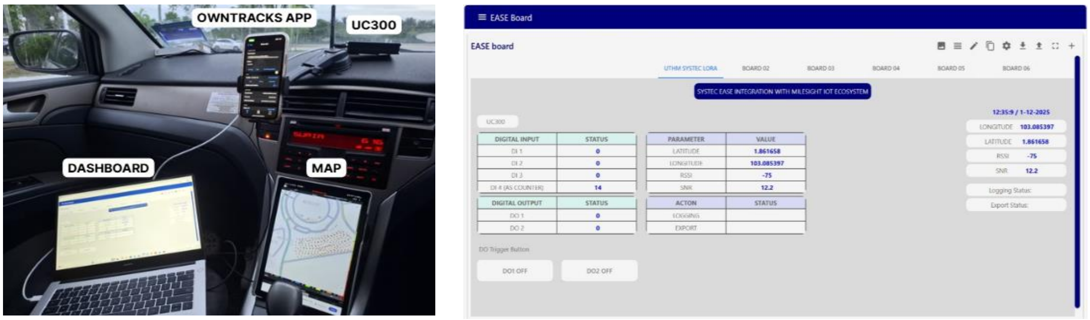


Fig. 4 *UC300 End Node and UG65 Gateway Communication Verification*

Evolution in Electrical and Electronic Engineering Vol. 7 No. 1 (2026) p. 154-161

2.2 Drive Test and Data Collection

The UC300 was connected to a laptop to provide a continuous power supply throughout the test. During the tests, the end node integrated with the OwnTracks App for location tracking, sent data in the form of latitude, longitude, RSSI, SNR, SF, and data rate every one minute interval to the UG65 gateway. The measurements were monitored by built-in Web GUI. Data collected by the gateway was logged and visualized on Systec Ease Cloud for easy export and analysis of network performance during the drive tests. Fig. 5 illustrates the drive test setup in (a) and the monitoring dashboard on Systec Ease Cloud in (b).



(a) (b)

Fig. 5 *Drive Test and Data Collection (a) Drive Test Setup; (b) Real-Time Monitoring Dashboard*

3. Results and Analysis

This section shows the performance of the LoRaWAN network from field measurements and machine learning predictions. It includes heatmaps of RSSI and SNR, correlation analysis, and feature importance are discussed to point out which factors have the most impact on the behavior of signals in NLOS environments in campuses. Furthermore, this section covers model training performance, predicted signal maps, and the comparison of measured and predicted values to evaluate the accuracy of predictions at unseen locations.

3.1 Actual Measurement Heatmaps

RSSI and SNR heatmaps were created for the entire UTHM campus and the Library Parking Zone as an example of an NLOS area. Fig. 6 (a) and (b) present the RSSI and SNR heatmaps for the entire campus to identify the overall coverage and areas of weak signals. Fig. 7 (a) and (b) illustrate the RSSI and SNR heatmap for Library Parking Zone where the signal strength is reduced due to buildings and obstacles. In general, the NLOS areas have lower RSSI and SNR values than the open spaces. For LoRaWAN, RSSI values ranging between -30 to -60 dBm are considered as good, RSSI values between -61 and -90 dBm are considered as moderate, while values less than or equal to -91 dBm are considered as poor. Similarly, SNR values that are greater than or equal to 0 dB are good, between -1 and -10 dB are categorized as moderate, and value of < -10 dB are classified as poor. These ranges are used to help interpret the heatmaps and identify regions that have strong or weak signal performance.

(a) (b)

Fig. 6 *Actual Measurement Heatmaps of Entire UTHM Campus; (a) RSSI (b) SNR*

(a) (b)

Fig. 7 *Actual Measurement Heatmaps of Library Parking Zone; (a) RSSI (b) SNR*

3.2 Correlation Analysis

Correlation analysis was performed to understand how different parameters affect LoRaWAN performance. Fig. 8 presents the correlation matrix heatmap that includes the correlation values between the distance-related features, neighboring signal parameters, and the measured RSSI and SNR.

From Fig.8, the Distance from End Node to Gateway has a negative correlation with RSSI (-0.58) and SNR (-0.57), which means that signal strength and quality are decreased with the increase of distance. The nearest distance to the gateway shows an even stronger negative correlation with RSSI (−0.71) and SNR (−0.74), highlighting the importance of distance in signal performance.

In comparison, nearest RSSI is strongly correlated with RSSI (0.82) and nearest SNR is strongly correlated with SNR (0.89). These strong positive correlations suggest that there are good indicators of local signal conditions in nearby signal measurements. RSSI and SNR are also highly correlated at 0.85, confirming their close relationship in assessing link quality.

Overall, the distance-related features and neighboring signal parameters have the strongest influence on LoRaWAN signal performance in NLOS campus environments, making it suitable inputs for the machine learning model.

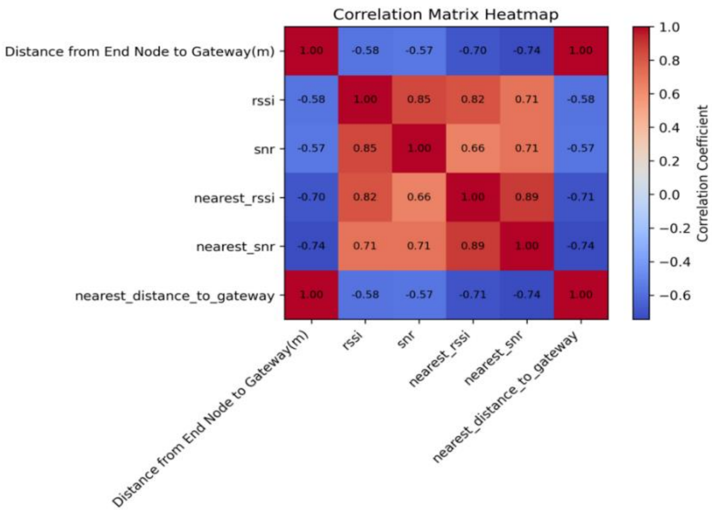


Fig. 8 *Correlation Matrix Heatmap of Input Features and LoRaWAN Signal Parameters*

3.3 Feature Importance

Feature importance analysis was performed using Random Forest model to identify the most influential input features for predicting RSSI and SNR. Table 1 shows the numerical feature importance values, which ranks each feature based on its contribution to the model predictions.

Nearest Neighbor RSSI is the most important feature with an importance value of 0.50 which means that the nearby signal strength has the most impact on the prediction results. This is followed by Nearest Neighbor SNR with an importance value of 0.34 showing that nearby signal quality also plays a significant role.

Distance-related features have lower importance values. The Distance from End Node to Gateway has an importance of 0.09, while the nearest distance to the gateway contributes 0.08. Although their influence is smaller

Evolution in Electrical and Electronic Engineering Vol. 7 No. 1 (2026) p. 154-161

compared to neighboring signal features, distance still affects signal performance, especially in NLOS environments.

Overall, the results indicate that neighboring signal information is more influential than distance alone for predicting LoRaWAN signal performance in campus environments. This supports the use of spatial and neighbour-based features in the proposed machine learning model.

Table 1 *Numerical Feature Importance Values*

No.	Feature	Importance
1	Nearest Neighbor RSSI (dBm)	0.499835
2	Nearest Neighbor SNR (dB)	0.335307
3	Distance from End Node to Gateway (m)	0.089422
4	Nearest Distance to Gateway (m)	0.075435

3.4 Machine Learning Model Training Performance

This section displays the performance of the Random Forest model for the prediction of RSSI and SNR in the UTHM LoRaWAN environment. KNN features were used to capture local signal patterns since RSSI and SNR are dependent on the location. The model was trained using different values of k from 1 to 9 to identify the best neighborhood size. Table 2 presents Mean Squared Error (MSE) and R^2 for each k.

The model shows its best performance at k = 9 where it has the lowest MSE value of 40.992 and the highest R^2 value of 0.7345. This means that the model is able to explain around 73% of the variation of the RSSI and SNR measurements. The results also indicate that the performance of the model is stable with different k values, meaning that there is no overfitting. Based on these findings, k = 9 offers the best tradeoff between capturing local signal patterns and keeping the prediction stable. Therefore, the Random Forest model k = 9 was chosen as the final model for the prediction of RSSI and SNR around the UTHM campus.

Table 2 *Random Forest Model Performance for Different KNN Neighborhood Sizes*

k value	MSE	R^2
1	57.142	0.6281
2	62.062	0.6051
3	53.556	0.6582
4	52.196	0.6470
5	50.442	0.6558
6	45.127	0.7044
7	45.498	0.7027
8	43.805	0.7140
9	40.992	0.7345

3.5 Predicted Heatmaps

Fig. 9 in (a) presents the predicted RSSI and SNR heatmap for the entire UTHM campus. The model involves the combination of RSSI and SNR to provide an overall LoRaWAN link quality. Areas with good signal (green) have RSSI ranging between -30 and -60 dBm and SNR ≥ 0 dB. Moderate signal areas (yellow) have RSSI -61 to -90 dbm or SNR -1 to -10 db and poor areas (red) have RSSI -91 to -120 dbm or SNR < -10 db. The map shows strong coverage near the gateway and weaker signals toward campus edges. The predicted heatmap is smoother than real measurements but captures the general coverage pattern well.

The predicted heatmap for the Library Parking area is shown in Fig. 9 in (b). The model identifies weak signal areas inside the parking zone and stronger signals near open roads. The predicted map shows both is in line with the trends in actual measurements. This result demonstrates that the model can reliably estimate LoRaWAN performance using nearest-neighbor features.

(a) **(b)**

Fig. 9 *Predicted RSSI and SNR Heatmaps ; (a) Entire UTHM Campus (b) Library Parking Zone*

3.6 Measured vs Predicted Comparison (NLOS performance)

Fig. 10 and Fig. 11 compare the measured and predicted RSSI and SNR in the Library Parking Zone. The predicted RSSI and SNR curves are smoother than the actual measurements, which reflects the fluctuations due to obstructions, multipath reflections and variability in the environment. Despite these local variations, the predictions represent the general trends and general behavior of the signals over distance. This means that the model is able to generalize well RSSI and SNR patterns and give good approximation of signal performance for unseen locations even though it is less sensitive to short term variations. Overall the predicted values are in good agreement with the measured data with slight deviations in extreme NLOS spots.

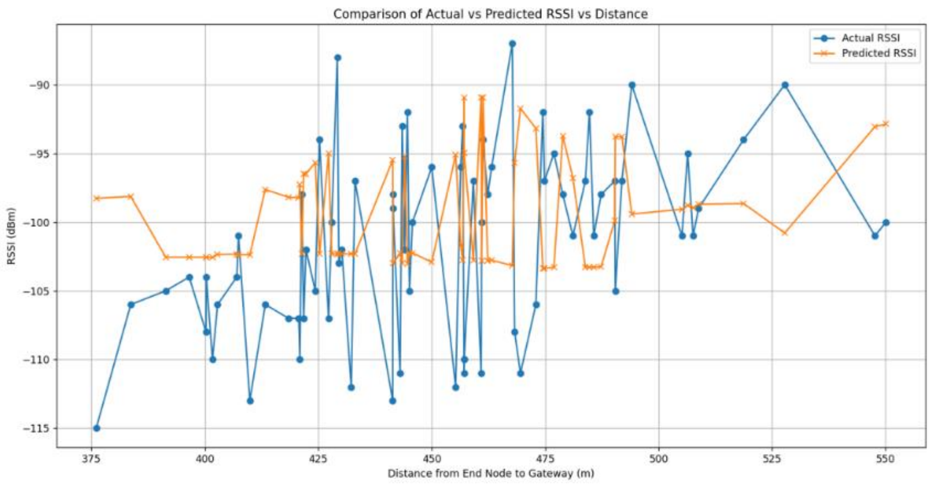


Fig. 10 *Comparison of Actual and Predicted RSSI Values (Unseen Dataset)*

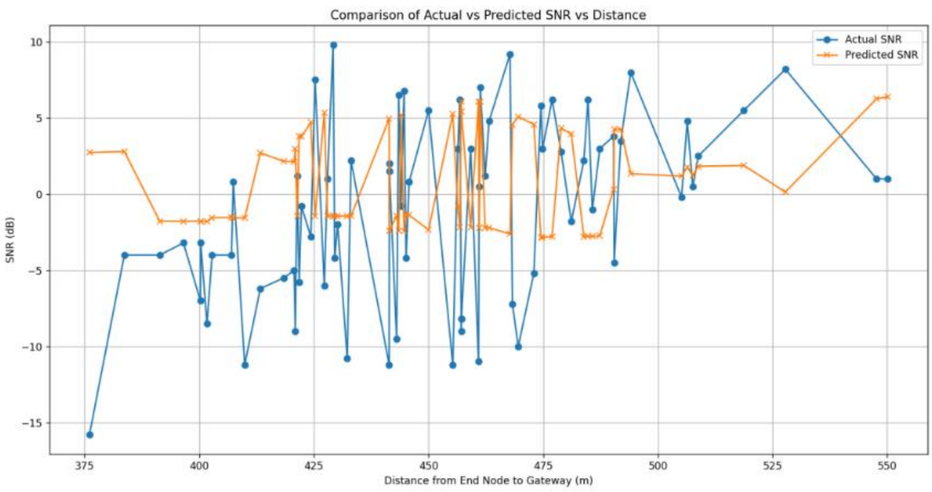


Fig. 11 *Comparison of Actual and Predicted SNR Values (Unseen Dataset)*

4. Conclusion

This paper presented a data-driven machine learning approach for predicting LoRaWAN signal performance in NLOS campus environments. By relying solely on measured signal data, the proposed model avoids the limitations of assumption-based propagation methods. The results show that the approach can effectively support LoRaWAN deployment optimization in complex real-world environments. Future work may further improve the model by incorporating additional environmental features or adaptive learning strategies.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The author confirms sole responsibility for the following: ***study conception and design, data collection, analysis and interpretation of results, and manuscript preparation:*** *Lubna Nazihah Binti Md Lajis. All authors reviewed the results and approved the final version of the manuscript.*

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