ADVANCE PATH LOSS MODEL FOR LORAWAN COVERAGE ESTIMATION

MÔ HÌNH SUY HAO NÂNG CAO TRONG ƯỚC TÍNH VÙNG PHỦ MẠNG LORAWAN

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Abstract - This paper demonstrates that, using multiple data points around each gateway allows for the creation of accurate coverage heat maps by using a proposed LoRaWAN coverage estimation algorithm. This method effectively identifies areas with varying signal strength across Da Nang City, highlighting where additional gateways are needed to improve network reliability. Unlike previous studies, this research considers environmental factors such as topography and urban structures, enhancing prediction accuracy. This technique would be essential for optimizing essential for optimizing LPWAN deployments and ensuring efficient resource utilization. Future efforts will focus on refining neural network models and integrating real-time data to support scalable Smart City solutions and a more robust connectivity infrastructure, with this work planned for future research.

Key words - LPWAN; LoRaWAN; LoRa; path loss; coverage.

Tóm tắt - Bài báo này chứng minh rằng, việc sử dụng nhiều điểm dữ liệu xung quanh mỗi gateway cho phép tạo ra các bản đồ nhiệt thể hiện vùng phủ sóng chính xác nhờ thuật toán ước lượng phủ sóng LoRaWAN được đề xuất. Phương pháp này được áp dụng để xác định hiệu quả các khu vực có cường độ tín hiệu khác nhau tại thành phố Đà Nẵng, làm nổi bật những vị trí cần thêm gateway để cải thiện độ tin cậy của mạng. Khác với các nghiên cứu trước đây, nghiên cứu này xem xét các yếu tố như môi trường, địa hình và cấu trúc đô thị, giúp nâng cao độ chính xác của dự đoán vùng phủ sóng. Kỹ thuật này rất quan trọng để tối ưu hóa việc triển khai mạng LPWAN và đảm bảo sử dụng tài nguyên hiệu quả. Các nghiên cứu trong tương lai sẽ tập trung vào việc tinh chỉnh các mô hình mạng nơ-ron và tích hợp dữ liệu thời gian thực để hỗ trợ các giải pháp thành phố thông minh và có thể mở rộng cơ sở hạ tầng kết nối một cách nhanh chóng.

Từ khóa - LPWAN; LoRaWAN; LoRa; suy hao; vùng phủ.

1. Introduction

Low Power Wide Area Networks (LPWANs) have recently garnered significant attention in Southeast Asia due to their distinctive qualities, including low power consumption, extensive coverage, and cost-effective deployment. Among these, LoRaWAN stands out as a globally standardized LPWAN technology, thanks to the efforts of the LoRa Alliance. LoRaWAN is particularly suitable for various IoT applications such as Smart Tourism, Smart Agriculture, and Smart Cities [1]. Da Nang, the fifth-largest city in Vietnam with over one million inhabitants, serves as the commercial and intellectual hub of Central Vietnam and is an ideal candidate for implementing such technologies.

To deploy numerous LoRaWAN gateways around a city, for example in a smart city application, accurately estimating LoRaWAN network coverage is crucial for effective planning and deployment, especially in urban and large areas. This estimation allows for the strategic placement of gateways to ensure optimal network performance and coverage. By understanding the coverage areas and potential signal gaps, planners can determine the most efficient locations for gateways to maximize connectivity and minimize interference. This approach not only improves the reliability and quality of the network but also ensures cost-effectiveness by preventing the over-deployment of gateways. Furthermore, accurate coverage estimation helps anticipate and address environmental factors and topographical challenges that may affect signal strength and reliability. Ultimately, thorough coverage estimation is essential for the successful implementation and scalability of LoRaWAN networks, supporting various IoT applications and enhancing the infrastructure of smart cities [1].

A critical aspect of deploying the Smart City model involves ensuring comprehensive network coverage across the entire city. The study in [2] investigates LoRaWAN network coverage through real-life measurements conducted in Oulu, Finland. This research measured the received signal strength from various locations within the city, demonstrating a maximum communication range of over 15 km on land and nearly 30 km on water. Another study [3] employs a combination of real-world measurements and high-fidelity simulations to show that three gateways are sufficient to cover a dense urban area within an approximately 15 km radius.

Research by [4] adopts a different approach by evaluating multiple simulation tools, including Xirio, Coverage Prediction and Analysis Software, Radio Mobile, and Tower Coverage, to determine the most suitable tool for LPWAN networks. Their findings indicate that the Xirio tool offers the most accurate coverage simulation for LoRaWAN technology. However, they suggest that the final evaluation should integrate simulation results with real-world measurements.

The study in [5] focuses on the coverage and capacity analysis of LoRaWAN for typical massive IoT applications in both urban and suburban areas, utilizing the simulation tool Forsk Atoll 3.3.2. Similarly, the research in [6] deploys a LoRaWAN network and assesses signal quality and coverage to identify blank spots on the map.

In another study, [7-8] introduces a cost-effective, open-source technical solution and measurement procedure for evaluating LoRaWAN network coverage in dense urban environments. By assessing connection link quality parameters, they developed a testing methodology to determine the operational coverage of the deployed network. The study by [9] implements an assessment of radio network coverage, aiming to propose a new methodology for selecting measurement points during coverage and signal quality assessments. Finally, the research in [10] provides recommendations for more effective network deployment by optimizing the use of LoRaWAN features, while the study in [11] analyzes LoRaWAN network signal coverage and quality parameters in real-time, using a case study of water quality monitoring along the Cikumpa River in Depok City.

Most of the research has concentrated on LoRaWAN network coverage using simulations and real-world measurements. However, these studies do not fully account for environmental factors influenced by topographical conditions. Additionally, the estimation of LoRaWAN network coverage based on real environmental conditions has not been thoroughly examined.

In this research, an estimation algorithm is proposed based on sparse coverage measurements to estimate LPWAN coverage, specifically for LoRaWAN networks. These new results are expected to assist in the network planning process, which is a crucial step before deploying a large number of gateways throughout a city.

2. LoRaWAN Deployment and Data Collection

The first step to obtaining a good estimation of network coverage is to collect data. To achieve this, an end device was used to record the RSSI (Received Signal Strength Indicator), SNR (Signal-to-Noise Ratio), and its own position. Then, a route through the city was created, which is a specific route was planned and mapped through the city to facilitate data collection and testing, aiming to gather the most relevant data for prediction. To maximize the value of the data, we tried to cover the entire city without retracing the same roads. While we aimed to maximize the spatial coverage by exploring diverse areas of the city, we also recognize the importance of collecting multiple measurements in the same locations under different environmental conditions, including varying weather, noise, and topographical influences, to better understand their impact on network reliability.

In this experiment, five LoRaWAN gateways were installed in the high building and top of mountain, and Gateways were operated on AS923-2 band, which includes Rak7240 and Kerlink iBTS with 3dBi Fiberglass Antenna. These gateways were installed around Da Nang City with location and altitude as shown in Table 1.

End device use in this experiment is a home-made UCA board as shown in Figure 1. This PCB was developed to ease connection between an Arduino Mini Pro, and an RFM95 LoRa module, an AA battery. The antenna on this PCB is a miniaturized, low-cost printed antenna, based on a meandered F antenna (IFA) structure with a peak directivity of 2.1 dBi and a peak gain of 0.9 dBi.

Table 1. *List of gateways in Da Nang City*

Gateway ID	Location	Altitude	Brand
Danangdrt	DRT Da Nang building	45m	Rak7240
rfthings-rak7240-79ed	DUT building	35m	Rak7240
7276ff002e06029f	DSP building	90m	Kerlink iBTS
7276ff002e0507da	Son Tra mountain	810m	Kerlink iBTS
trungnam	Trung Nam building	80m	Rak7240

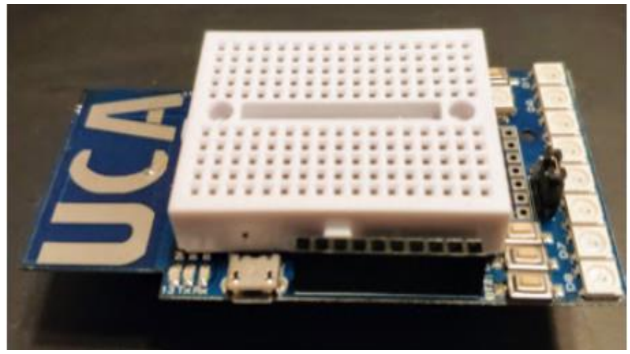

Figure 1. *UCA board for data collection in Da Nang City*

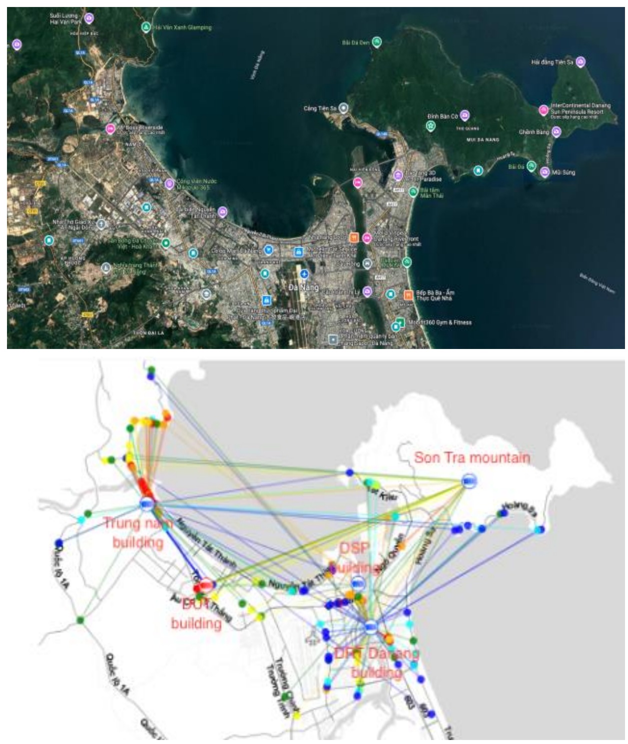

Figure 2. *Data collection and terrain information*

Data collection, as described in Figure 2, involved traversing the city on a motorbike equipped with a calibrated reference antenna, which was modified to be suitable for the 920-923 MHz band. The UCA device is held by the hand of the person sitting behind. This method ensured accurate measurement of RSSI and Signal-to-Noise Ratio (SNR) across various locations. The motorcycle route was meticulously planned to cover diverse urban landscapes, including areas characterized by tall buildings, open spaces, and potential signal obstructions.

Our approach focused on capturing comprehensive data to support accurate prediction models. By avoiding duplicate routes and ensuring geographical diversity in our data collection, we aimed to provide a holistic view of network performance across Da Nang. This detailed dataset serves as the foundation for our ongoing efforts to optimize network deployment strategies and enhance connectivity reliability in urban environments.

3. Proposed algorithm

RSSI ranging methods commonly used are based on theoretical models such as the free space propagation path loss model and the logarithmic normal shadowing model [9]. However, the application environment of wireless sensor signals is not in free space but in real-world settings such as industrial sites or indoor buildings. In these environments, it is necessary to consider factors such as shading, obstacle absorption, and interference from scattered reflections. The attenuation characteristics of channels over long distances follow a lognormal distribution, which is commonly modeled using the logarithmic normal block model. The path loss model is as follows [9]:

$$PL\,(d_0) = PL(d) + 10nlog\left(\frac{d}{d_0}\right) + X_\sigma \quad (1)$$

In this formula, PL(d) represents the path loss of the received signal at a distance d (meters). It is given as an absolute power value in dBm. PL(d_0) denotes the path loss of the received signal at the reference distance d_0. The term n is the path loss exponent specific to the environment, indicating the rate at which path loss increases with the distance d. X_σ is in dB and accounts for the shadowing effect, with a standard deviation typically ranging from 4 to 10 and a mean value of 0. A larger value of implies greater model uncertainty. The signal strength at the receiving nodes is given by:

$$RSSI = P_t - PL(d) \quad (2)$$

In this formula, P_t represents the signal transmission power, and $PL(d)$ indicates the path loss at a distance d, both are measured in dBm. Let A represents the signal strength received from reference nodes at the distance d_0. The expression for A is as follows:

$$A = P_t - PL(d_0) \quad (3)$$

The path loss model, measured at the actual distance d (meters), is as follows:

$$P(d) = P(d_0) - 10nlog\left(\frac{d}{d_0}\right) - X_\sigma \quad (4)$$

In this formula, PL(d) represents the received signal strength when the actual distance measured is d (meters). PL(d_0) represents the received signal strength at the reference distance d_0. The term X_σ denotes a random variable following a normal distribution with mean 0 and variance σ^2.

We set the reference distance d_0 = 1 m, as derived from formulas (3) and (5).

$$RSSI = A - 10nlog\left(\frac{d}{d_0}\right) - X_\sigma \quad (5)$$

The distance can be calculated using the formula:

$$d = 10^{\frac{A-RSSI}{10n}} \quad (6)$$

In our proposed algorithm, we work with each gateway separately. For each gateway, we choose an arbitrary point. We denote $RSSI_{ref}$ and d_{ref} as its values.

Let n be the environmental variable related to a point and a gateway. Based on the formula (5), the core of the algorithm is as follows:

$$RSSI = RSSI_{ref} - 10nlog\left(\frac{d}{d_{ref}}\right) \quad (7)$$

It means that for any point, if we know its environmental variable we can determine its RSSI. To determine the environmental variable, we separate the dataset on two groups:

The training dataset and the testing dataset. For each training data we can calculate the environmental variable because we know its position and its RSSI.

We use the following equation for the training dataset:

$$n_{train} = \frac{RSSI_{ref} - RSSI}{10\log\left(\frac{d}{d_{ref}}\right)} \quad (8)$$

Now that we know the environmental variable of the training set, we can estimate the environment variables for each data of the testing set with this equation:

$$n_{test} = \frac{\sum_{i=0}^{n} Coeff(i) * n(i)}{\sum_{i=0}^{n} Coeff(i)} \quad (9)$$

With n(i) is the environmental variable of the training data number i. Coeff(i) is calculated as follow:

$$Coeff(i) = e^{(800-Distance_{min})^2 - (800-Distance(i))^2} \quad (10)$$

$Distance(i)$ is the distance between training data number i and the testing data. $Distance_{min}$ is the distance between our testing data and its nearest training data.

This way of calculating n_{test}takes into account all the $data_{train}$ but will highly prioritize the nearest points, where the environment should be similar.

Now that we have n_{test}, we can easily calculate $RSSI_{test}$ with Equation (8). We can use the same method to calculate the SNR and we get:

$$Signal = \ RSSI\ if\ SNR > 0 \quad (11)$$

$$Signal = RSSI + SNR\ if\ SNR < 0 \quad (12)$$

To get the total signal we take the maximum signal of all gateways:

$$Signal_{total} = \max\left(signal(i)\right) \quad (13)$$

The proposed algorithm was implemented using a Python script, which is publicly available on GitHub at the following the link: https://github.com/Lic-Tran-Van/LoRaWANCoverageEstimation.git

The RSSI depends on the distance between the gateway and the measurement point, as shown in Figure 3, and this relationship is used in our prediction models. In this figure, RSSI typically decreases as the distance between the gateway and the end device increases. However, the relationship between RSSI and distance is not strictly linear. This means that for each doubling of the distance, the signal strength does not simply halve but decreases by a certain factor, often modeled logarithmically. This relationship is influenced by free-space path loss, obstacles, environmental interference, and other factors that cause signal attenuation [2].

In the context of a path loss model, "n" refers to the path loss exponent, a key parameter that characterizes how the signal strength decays as it propagates through the environment. The value of n depends on the specific environmental conditions and is influenced by factors such as topography, urban structures, and other physical obstacles. In free space (i.e., an unobstructed environment), n is typically 2, as the signal strength decreases proportionally to the square of the distance from the transmitter (i.e., inverse square law). In urban or indoor environments, n is usually greater than 2, ranging from 2.7 to 4 or higher, because of the increased signal attenuation caused by factors like buildings, walls, and other obstructions. Additionally, n can be influenced by weather conditions (e.g., rain or fog), which can further attenuate the signal. For instance, in a rainy environment, the path loss exponent can increase because the signal is absorbed or scattered by raindrops. Similarly, noise from other devices or environmental factors can add uncertainty to the signal strength, impacting the accuracy of path loss models.

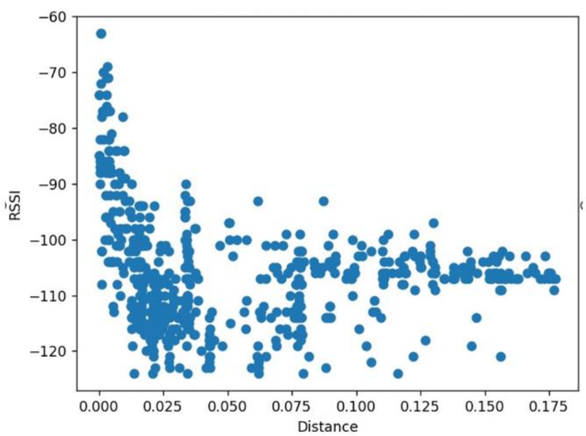

Figure 3. *Distance vs RSSI*

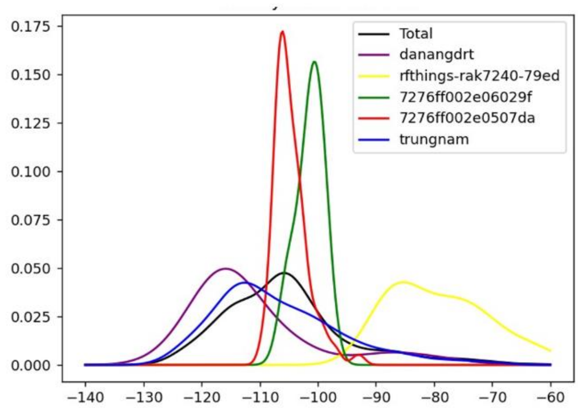

Figure 4. *Density plot of RSSI*

The data stored in a CSV file via TTN Mapper was used to generate the density plots of RSSI and SNR for each gateway. Figure 4 shows the density plot of RSSI (Received Signal Strength Indicator) values for each gateway, as depicted in the attached image, illustrates the distribution and concentration of RSSI measurements across different gateways. The plot includes six different gateways: 'Total', 'danangdrt', 'rfthings-rak7240-79ed', '7276ff002e06029f', '7276ff002e0507da', and 'trungnam', each represented by a unique color. The black line, representing the 'Total' distribution, provides an overall view of RSSI values across all gateways, showing a broad peak around -110 dBm. 'danangdrt' (purple) and 'trungnam' (blue) display similar distributions with peaks slightly left-shifted relative to the 'Total' distribution, suggesting somewhat stronger signals. The 'rfthings-rak7240-79ed' (yellow) shows a much wider distribution with a notable peak around -95 dBm, indicating varied signal strengths with a tendency towards stronger RSSI values. The gateways '7276ff002e06029f' (green) and '7276ff002e0507da' (red) exhibit the highest peaks around -100 dBm and -105 dBm, respectively, indicating very strong and concentrated signal strengths.

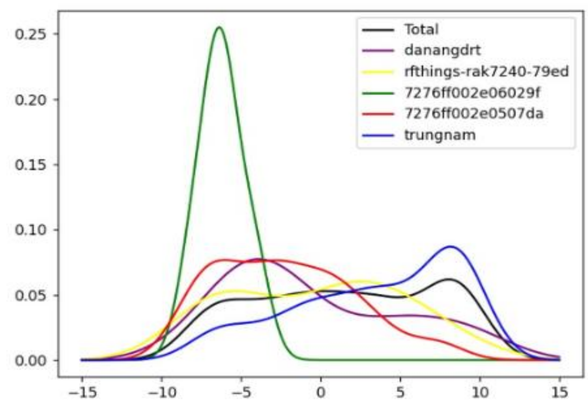

Figure 5. *Density plot of SNR*

These variations highlight the differences in signal reception quality among the gateways, with some capturing stronger and more consistent signals compared to others. The overall shape and spread of the density plots provide insights into the reliability and performance of each gateway in terms of RSSI.

The density plot of SNR (Signal-to-Noise Ratio) values for each gateway, as shown in Figure 5 illustrates the distribution and variability of SNR measurements across different gateways. The 'Total' distribution, represented by the black line, shows a broad spread of SNR values with peaks around -5 dB and another smaller peak around 7 dB, indicating a diverse range of signal qualities. 'danangdrt' (purple) and 'trungnam' (blue) have more dispersed distributions with peaks at different points, suggesting varied signal-to-noise environments. Specifically, 'trungnam' has a notable peak around 10 dB, indicating better signal quality in some instances. 'Rftthings-rak7240-79ed' (yellow) displays a broad distribution with multiple peaks, particularly around -7 dB and slightly above 0 dB, reflecting fluctuations in signal quality. The gateways '7276ff002e06029f' (green) and '7276ff002e0507da' (red) show more defined peaks, with '7276ff002e06029f' having a prominent peak around -7 dB, indicating consistent signal reception within a narrower range. '7276ff002e0507da' displays multiple peaks, with the highest around -6 dB, suggesting it experiences various levels of signal quality. The gateway's SNR (Signal-to-Noise Ratio) plays a critical role in network performance. A high SNR (above 20 dB) indicates strong, clear signals, resulting in reliable communication, higher throughput, and low latency. A moderate SNR (10-20 dB) suggests acceptable performance but may experience occasional packet loss or slower speeds due to some interference. A low SNR (below 10 dB) indicates poor signal quality, leading to higher error rates, reduced throughput, increased latency, and connection instability, which negatively impacts overall network performance.

The dataset comprises 400 data points divided into two subsets: 80 % of the data serves as training data, and the remaining 20 % is allocated for testing purposes. The prediction model's accuracy, depicted in Figure 6 shows a mean error of 4.5, indicating its effectiveness in estimating signal strengths across Da Nang City. While this error is evident, additional data acquisition is anticipated to notably reduce it.

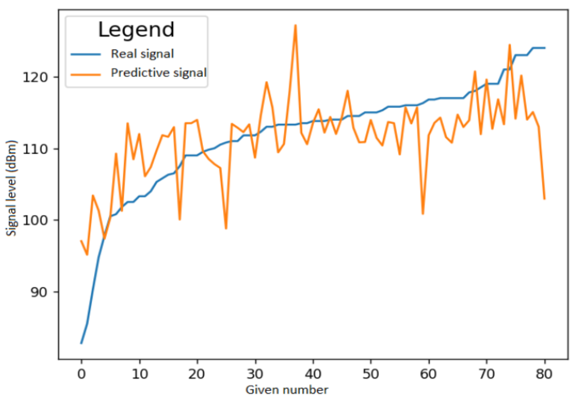

Figure 6. *Results of the prediction on the testing data for over 400 data points*

To achieve a more uniform and detailed coverage map, additional steps in data processing are crucial. This includes employing advanced algorithms to refine signal predictions based on factors such as topography, building density, and environmental conditions. By integrating more comprehensive data sets and leveraging sophisticated analytical techniques, we aim to enhance the accuracy and reliability of our coverage maps.

Figures 7 and 8 visually display the predicted data points for the gateways danangdrt and trungnam, respectively. The total coverage of all gateways was estimated using Formula 13 and is depicted in Figure 9, showing predictions across 10,000 points scattered throughout the city. These maps provide a broad overview of the predicted coverage, demonstrating that our model accurately captures the general signal distribution.

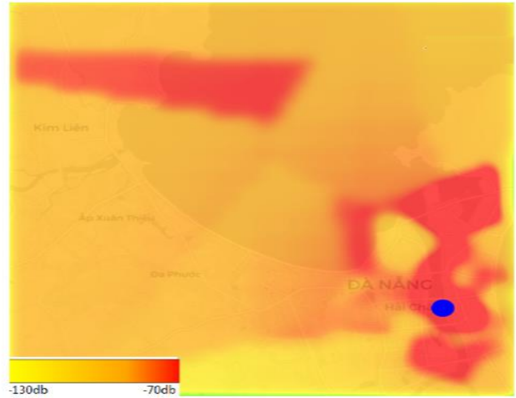

Figure 7. *Da Nang coverage estimation by the Gateway danangdrt*

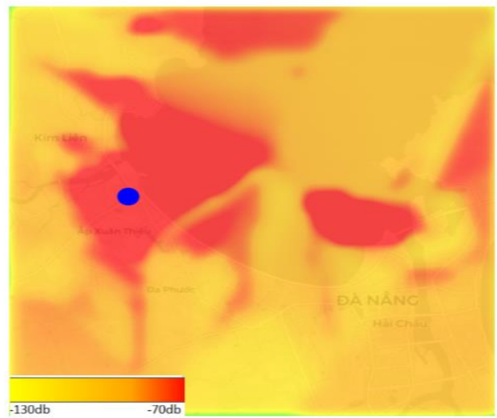

Figure 8. *Da Nang coverage estimation by the Gateway trungnam*

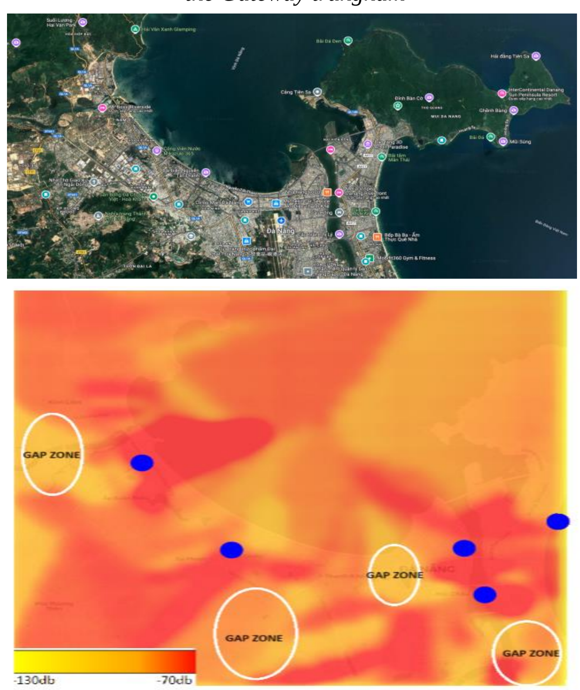

Figure 9. *Da Nang coverage estimation with all gateways and Identification of gap zones*

Based on the coverage estimation with all gateways, it is easy to identify gap zones, also known as coverage holes or dead zones, where the LoRaWAN signal is weak or entirely absent. The gap zones are shown in Figure 10. To improve coverage, it is necessary to install additional gateways in these gap zones. Once gap zones are identified, the next step is to plan the gateway deployment strategically. This includes determining areas where additional gateways are needed and areas where gateways can be relocated for better coverage. This approach helps optimize LPWAN deployments and ensures more efficient resource utilization.

4. Conclusion

The findings demonstrate that employing multiple data points around each gateway enables us to generate accurate coverage heat maps by proposed LoRaWAN estimation coverage algorithm. This tool proves invaluable for identifying areas with strong or weak signal coverage across Da Nang City. By visualizing these heat maps, stakeholders can pinpoint locations where additional gateways are necessary to enhance network robustness and reliability. Several studies on the evaluation of simulation tools for LPWAN coverage have already been published. However, these studies do not consider environmental factors that depend on the topography of the land. In Da Nang, mountainous areas, tall buildings in some neighborhoods, and noisy environments impair signal strength. It is therefore essential to consider these factors to make accurate predictions. Our approach highlights the effectiveness of machine learning in predicting signal strength variations across urban landscapes. This predictive capability is crucial for optimizing LPWAN deployment strategies, ensuring efficient utilization of resources and improving overall network performance. Moving forward, ongoing refinement of our proposed algorithm and continuous data collection efforts will be pivotal in refining our coverage estimation methodology. By integrating real-time data and leveraging advanced analytics, we aim to provide scalable solutions that meet the evolving demands of Smart City initiatives in Da Nang and similar urban environments.

In conclusion, our study underscores the potential of proposed algorithm-based heat mapping as a strategic tool for planning and optimizing LPWAN deployments. By leveraging these insights, cities can achieve comprehensive coverage and enhance connectivity infrastructure to support the burgeoning IoT ecosystem effectively.

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