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LORAWAN-BASED RSSI-TRILATERATION MODEL FOR NODE LOCATION: A SIMULATION INTEGRATING FLORA AND OMNET++

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This work presents the employing of LoRaWAN (Long Range Wide Area Network) for location applications through a network simulation to determine a mobile node position. We rely on FLoRa (Framework for LoRa) and OMNeT++ (Objective Modular Network Testbed in C++) simulator, which uses Python feature tools, following the calculation of node placement using the trilateration technique. Our method differs from others in that we calculate the FLoRa power loss and determine different simulation settings using the shadowing feature of the log-distance path loss model. We approached RSSI (Received Signal Strength Indicator) to measure the distance between the LoRa gateways and the nodes, establishing a link between these parameters. Our work aims to promote the integration of open-source tools for verifying signal intensity values based on node distance from gateways. We consider it useful for engineers in predicting signal behaviors according to topology and settings variations. During the experimentation, the network underwent different performances according to the transmission parameters considered during the simulation. This was critical when increasing the number of mobile nodes, leading to consuming computer capacity and resources. Through repetition of tests, we confirmed the lower intensity of the received signal as the node moves to farther positions, reaching consistent power indicators and positioning accuracy. Overall, the results show that LoRaWAN integrated with trilateration techniques can be practical in providing adequate performance for node positioning accuracy and long-distance communication with low power consumption.

Keywords: Framework for LoRa, low-power technologies, OMNeT++, path loss, RSSI

1. Introduction

Different wireless technologies enable tracking in both indoor and outdoor areas, employing positioning techniques to locate vehicles, individuals, or animal species (Asaad & Maghdid, 2022; Bäßmann *et al.*, 2023; Maduranga & Sithara, 2022; Sanchez Padilla *et al.*, 2020). Knowing vehicle locations are useful for predicting or assessing supply chain efficacy in transportation systems (Liu *et al.*, 2023) or schedule predictions (Mero Cheme *et al.*, 2022). For people tracking, it can be suitable for analysing path behaviours, law enforcement monitoring, or elderly caring (Nguyen *et al.*, 2020; Sun *et al.*, 2023; Wijnberg & Le-Khac, 2021). For animal tracking, biologists may find it useful to locate terrestrial or marine species during different seasons for the purpose to study their activity and reproduction habits across a large area (Acácio *et al.*, 2022; Coutinho & Boukerche, 2021).

Because of its high accuracy location, researchers see the GPS (Global Positioning System) as one of the most prominent satellite-based radio navigation technologies for a variety of wireless tracking applications (Gurulakshmi *et al.*, 2023; Raiyn, 2017). However, the contract of transponders related with carriers can bring positioning privacy issues that end-users face towards the use of associated services, threating the autonomy of the wireless network (Frattasi & Della Rosa, 2017). We also must consider that accuracy is not attained due to environmental issues that positioning devices cope according to the supporting technology, affected especially due to atmospheric conditions that causes problem in the signal transmission, challenging vast applications including underwater navigation (Kinsey *et al.*, 2006). In addition, the high-power consumption of this wireless communication technology reduces the battery life of the devices due to the charge and discharge cycles they go through, limiting the usefulness of the positioning devices (Tan *et al.*, 2019; Van Mulders *et al.*, 2022).

The number of devices connected to the Internet is continuously growing at an exponential rate (Verma *et al.*, 2017). Large-scale connectivity requires communication systems that can work over long distances and withstand large numbers of simultaneously connected devices (Silva *et al.*, 2021). To be economically and environmentally feasible, each network device's energy usage must be optimized. We have LPWAN (Low-Power Wide-Area Network) networks as a solution to these criteria, with LoRaWAN (Long Range Wide Area Network) being one of its most popular technologies. LoRaWAN topologies are typically deployed in areas wherein traditional network coverage is limited to offer communication between low-power consumption devices. This technique also focuses on geopositioning using trilateration to achieve low-energy consumption functionality for sector coverage where other wireless communications are not practical. Therefore, LoRaWAN becomes an alternative to GPS networks for determining the location of an object or person using tracking capabilities. Since batteries require constant energy recharging, the fact that some wireless technologies consume a lot of energy may cause environmental problems (Mohd Aman *et al.*, 2021). It is required to configure communications using alternate methods that do not require constant battery recharging, hence extending the devices' usable life. Thus, it benefits the environment and end-users since it consumes less power, extending battery life and reducing energy waste (Silva *et al.*, 2021).

Networks based on low-power technologies enables the development of long-distance wireless topologies with low energy consumption (Bahashwan *et al.*, 2021; Kabalci & Ali, 2019). Due to its application in the IoT (Internet of Things), the implementation of topologies based on these technologies has grown significantly in recent years. To make implementations commercially viable, IoT requires wireless communication technologies that support large numbers of synchronously connected devices in order to achieve long-distance communication utilizing low-energy resources (Mekki *et al.*, 2019; Silva *et al.*, 2021). Capabilities of low-power devices are deemed in a variety of applications, including asset tracking (Carvalho *et al.*, 2018), agriculture (Liya & Arjun, 2020), environmental surveillance (Roque & Sanchez Padilla, 2020), and smart cities (Ferreira *et al.*, 2019). Also, due of its ability to overcome multipath and interference limits, as well as its performance through RSSI (Received Signal Strength Indicator), including outdoor scenarios, LoRaWAN is becoming a popular alternative among proprietary and standard-based technologies (Farahsari *et al.*, 2022; Mekki *et al.*, 2019).

Using a trilateration technique for positioning computation, we set up a LoRaWAN topology with three gateways following a framework, obtaining a relationship between the node distance and the RSSI to relate the equation systems with the trilateration mathematic technique (Ismail *et al.*, 2019). We considered trilateration because it is easier to implement for positioning systems and obtain parameters, such as location, velocity, and elevation of nodes through the continuous transmission of radio signals from multiple nodes using the geometry of circles, spheres, and triangles to get the most accurate position (Bhardwaj *et al.*, 2020). Constraints can arise from the modelling environment since it is difficult to examine all the possible variables that affect a system, such as the *log-distance path loss with the shadowing* model for signal loss propagation prediction.

Our objective is to illustrate a LoRaWAN network using an end-to-end software-based Framework for LoRa, known as FLoRa (Framework for LoRa) (FLoRa, n.d.), with OMNeT++ (Objective Modular Network Testbed in C++) for determining a mobile node location simulating outdoor environments in different settings and criteria. Through this work, we encourage the integration of these open-source tools to verify signal intensity values according to the distance of the nodes concerning the gateways, which can become valuable for engineers to forecast signal behaviours through the setting of different topologies and conditions.

2. Related work

Sadowski & Spachos (2018) present a comparison performance of wireless technologies for indoor and long-distance wide-area network positioning, which included LoRaWAN. When employing IoT devices, the comparison was according to localization accuracy and power consumption. The RSSI values received from each modality followed by trilateration to determine position. The LoRaWAN architecture includes four Arduinos operating with the Dragino LoRa Shield, one acting as a receiver and the others as transmitters, each with its respective address. The receiving node continually monitored the channel for messages. When receiving the information, the RSSI was measured and conveyed to the Arduino serial along with the message transmitted by the related node. They determine the path loss models in the surroundings for each of the several wireless communication technologies for the experiment. During the comparison, the long-range performance with LoRaWAN had an overall error of 1.190 meters that varied

according to the testing set but presented an energy consumption performance about 19.53 mW in average, through settings that can be an indicator for indoor location system deployments.

Kwasme & Ekin (2019) investigated LoRaWAN RSSI-based localization and assessed its accuracy, shortcomings, and possibilities using Software-Defined Radio (SDR) for path-loss characterization. Their method drew on multilateration to determine location via a LoRaWAN architecture that included a gateway for Wi-Fi connectivity in the 915 MHz band for bi-directional communication, microcontrollers, a mobile IoT node, a network tester, and USRPs to configure the SDR, with three to six base stations. Including a path-loss exponent calculation with five hundred RSSI readings, their findings show that LoRaWAN has a substantial localization error due to frequency hopping, making it unsuitable for applications requiring highly accurate positioning. Thus, they remarked that for applications that do not require high accuracy in localization, LoRaWAN provides an affordable and acceptable option, particularly for large-scale deployments.

On the other hand, case studies examine the viability of LoRaWAN as a localization solution for industrial work safety applications from many perspectives. Svertoka *et al.* (2022) present measures testing work led by two European institutions, including in their methodology location-based methods, such as trilateration and weighted-centroid algorithms, as well as the k-NN algorithm as a machine learning classifier. They covered testing in indoor and outdoor environments at those institutions, demonstrating the practical limitations of placement in standalone and k-NN driven localization systems. Although their findings show that LoRaWAN-based localization accuracy is equivalent to other Wi-Fi- and Bluetooth (BLE)-based solutions but with comparable losses in indoor and outdoor localization testing, they suggest LoRaWAN architectures for mixed environments complemented with other wireless technologies to achieve accurate positioning.

3. Methodology

The methodology followed is type-experimental since the objective was to simulate a LoRaWAN topology for calculating the mobile node position using trilateration. We sought to address this long-range technology as an energy-efficient outdoor tracking technology with great accuracy. We advise addressing this technology to acquiring the location of mobile nodes, so avoiding the negative effects that could result from technological waste due to the limited lifetime lithium batteries experience in order stakeholders from different fields may test the capabilities of LoRaWAN using a simulation. The communication topology was simulated using OMNeT++. The nodes, gateways, and servers were configured using the FLoRa simulation model.

To calculate the mobile node location, we used a Python script to process the power data provided by FLoRa. The model architecture was divided into three stages. First, in the LoRaWAN simulation, the tests integrated OMNeT++ and FLoRa to evaluate energy usage and RSSI. Then, using the position calculation, we relied on the power values obtained from the first stage simulation to code it in the Python script to seek node positioning. Finally, the precision computation enabled us to analyse the accuracy by comparing the calculated and real-time positions. Figure 1 shows the model architecture.

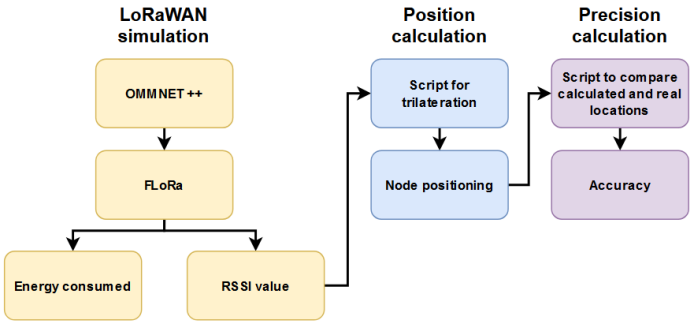


Figure 1. Model architecture

3.1. Network considerations

We used FLoRa with OMNeT++ for network simulation, with the former acting as an installable LoRaWAN topology model, beneficial for simulating this type of network through the integration of nodes, gateways, and a data conveyance model in an open medium. Furthermore, it enabled the configuration of

mobile nodes, including the visualization of the energy consumption of network nodes to validate power usage. As depicted in Figure 2, we followed a network layout set up for the simulation, which was modified according to conditions. We determined the location through trilateration, which indicates the location where the node had at least three antennas covered. Thus, the design of the LoRaWAN topology required the following:

- Three gateways that serve as the three necessary antennas for RSSI-based position estimation.
- A mobile node that moves in a fixed radius circumference.
- A router that serves as a data concentrator obtained by the three gateways.
- An intermediate network between the hub and main server that acts as the Internet provider.
- A server-side router that communicates the internet network with the main server.
- The main server.

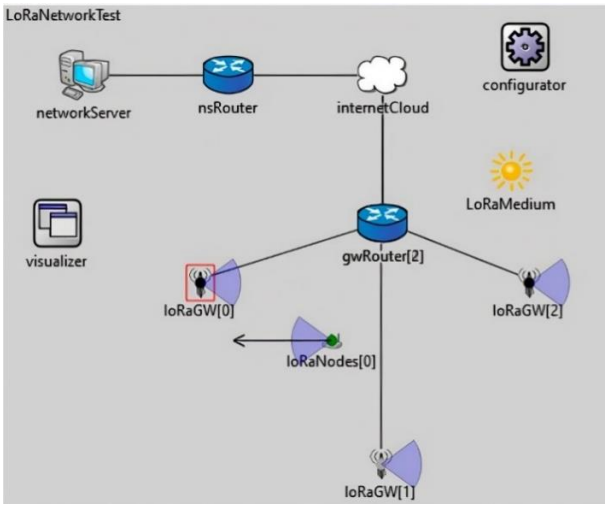


Figure 2. OMNeT++ based LoRaWAN design

We chose this setting because it meets the components to test the functionality of the theoretical requirements to show that locating a mobile node through LoRaWAN is feasible. Although the INET Framework 4.4 (INET, n.d.) supports multiple mobility criteria, we chose circular mobility for the visual ease of perceiving the node mobility and guaranteeing that it does not leave the coverage area of the fixed gateways. Figure 3 depicts a generic process that we established to obtain the node position value.

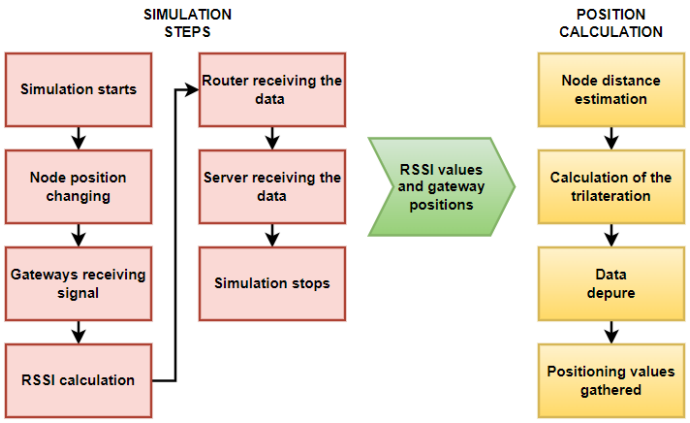


Figure 3. Node positioning process

3.2. Position and precision calculations

We established a two-dimensional position calculation for trilateration. Each gateway served as an antenna, producing a wavelength that spread as a circumference whose radius increased until it reached the target. There were unlimited solutions because it specified a particular radius circumference whose answer

was any point on the circumference. If we increased the number of gateways to two, any crossing on the perimeter would be the target. When we incremented to three gateways, the three circumferences intersected at a single point, finding the target position. Mathematically, we modelled it with the three equations depicted in equations 1, 2, and 3, where the system solution is the node position. By process repetition, it was possible to calculate the mobile node position, represented by x and y, where the pairs x_i, y_i represent the position of the three gateway antennas, while r_i represents the distance from the gateways to the node. The number of antennas is represented by i, e.g., i will take the values 0, 1, and 2 if we have three antennas in the network topology.

$$(x - x_0)^2 + (y - y_o)^2 = (r_0)^2. \quad (1)$$

$$(x - x_1)^2 + (y - y_1)^2 = (r_1)^2. \quad (2)$$

$$(x - x_2)^2 + (y - y_2)^2 = (r_2)^2. \quad (3)$$

To simplify the code implementation, we combined the equations algebraically in such a way that we obtained equations 4 and 5, whereas equations 6 to 11 represent the coefficient values. These equations are combined in a Python script to perform the trilateration calculation.

$$x = \frac{CE - FB}{EA - BD}. \quad (4)$$

$$y = \frac{CD - AF}{BD - AE}. \quad (5)$$

$$A = -2x_0 + 2x_1. \quad (6)$$

$$B = -2y_0 + 2y_1. \quad (7)$$

$$C = r_0^2 - r_1^2 - x_0^2 + x_1^2 - y_0^2 + y_1^2. \quad (8)$$

$$D = -2x_1 + 2x_2. \quad (9)$$

$$E = -2y_1 + 2y_2. \quad (10)$$

$$F = r_1^2 - r_2^2 - x_1^2 + x_2^2 - y_1^2 + y_2^2. \quad (11)$$

As the first inclusion criteria, we deemed the localization method based on solving the trilateration problem using RSSI. The reason was its modelling simplicity and because FLoRa provided the RSSI values to obtain the distance from the gateway to the node to solve the equation system shown in 1, 2, and 3. A second inclusion criterion was that the trajectory traced by the node be deterministic. We used a circumference for our work, but it could be any trajectory in which we knew all its path points to check if the calculated values were close to the real ones.

On the other hand, we can mention as an exclusion criterion the location methods not based on the trilateration problem solving using RSSI since their modelling and implementation are more complex, such as ToA (Time of Arrival) and TDoA (Time Difference of Arrival), even if they can achieve highly positioning accuracy (Wu *et al.*, 2019). An additional exclusion criterion was that the node path is probabilistic because there would not be reproducibility, making it impossible to check the values of the calculated position with the real one.

The differentiating factor of our proposal is that we approach the *log-distance path loss model* with shadowing feature (Rappaport, 2002). It allowed us to calculate the FLoRa power loss (equation 12) through the setting up of different simulation conditions. This model gathers variables, such as the $\overline{PL}(d_0)$ as the average power loss for the distance d_0, n as the power loss exponent, and X_σ as a normal random variable with standard deviation σ. We applied the parameters recommended by Slabicki *et al.* (2018) depicted in Table 1. These values are based on measurements taken partially indoors in built-up urban environments and in sub-urban areas with few tall buildings where LoRa networks were expected to include large number of devices exchanging data through the LoRa physical layer.

$$PL(d_0) = \overline{PL}(d_0) + 10n \log\left(\frac{d}{d_0}\right) + X_\sigma. \quad (12)$$

Table 1. Default parameter values for the power loss model (Slabicki *et al.*, 2018)

Scenario	d_0 **[m]**	$\overline{PL}(d_0)$ **[dB]**	n	**σ [dB]**
Urban	40	127.41	2.08	3.57
Suburban	1000	128.95	2.32	7.08

We calculated the mobile node position precision to compare LoRaWAN with GPS. As the node path was deterministic, the accurate node positions were the circumference points. We calculated the experimental error at each node point to average them later. We obtained the position as coordinates (x,y) to set a relationship between the experimental and actual position by equation 13 to find the Euclidean distance between two points. This was necessary to obtain the most relevant error definition when a line of sight exists among true and estimated positions (Mendoza-Silva *et al.*, 2021), wherein (x_c, y_c) is the calculated position and (x_r, y_r) is the actual position.

$$\sqrt{(x_r - x_C)^2 + (y_r - y_C)^2}. \quad (13)$$

3.3. Performance metrics and simulations

We measured the node power consumption in the LoRaWAN topology and the precision of the location calculation as a metric of the platform evaluation to confirm that it consumed less power than GPS to compare the precision. Since our objective was to simulate LoRaWAN, data concerning GPS power consumption can be obtained from the literature. We conducted a proof-of-concept to show this long-range technology as a competitive alternative to GPS for location, highlighting that we determined FLoRa's energy consumption in milliwatts. Even though we ran the simulations multiple times (more than three times each test) in a fixed radio through controlled conditions, such as the spread factor, node velocity, and antenna gains, we obtained constant energy consumption values. These values were not a software error outcome and confirmed the expected results. Likewise, we followed the same procedure to verify the accuracy.

The simulations drew on the elements described for the network considerations. OMNeT++ has three modes available to run a LoRaWAN simulation (Varga, 2019). These modes allow to configure parameters according to the project needs. The first is *Normal Run*, which supports simulations with all the corresponding live actions for an attractive visualization and recordings from the networks' events. The second one is *Fast Run*, which runs the simulation quickly without showing actions but recording certain network events. Finally, the third way is *Express Run*, which is the is the fastest way to run the simulation because it has the restriction of not displaying the actions, not recording the network's events, and only showing the time it took to complete the simulation.

For the LoRaWAN network simulation, we run it through the *Normal Run* mode. This mode granted us to see the node mobility and the network events through the console and to obtain the energy consumption values and the RSSI of the gateways and nodes. It made it possible to complete the simulation in less than two minutes. The number of nodes that the simulation can stand depends on the hardware capacity, and according to the literature, FLoRa developers have achieved testing with a maximum of 700 nodes.

4. Results

We focus our results on the simulation performance, addressing the limitations experienced regarding increasing the mobile nodes. Based on the signal intensity values we gathered, we depict an RSSI relationship concerning the distance from the gateways to the node. In addition, we tested the power consumption and the node position obtained calculated by the trilateration, including the actual positioning and positioning error values.

4.1. Network capacity

The transmission length, packet repetitions, frame size, simulation length, and packet conveying time were among the parameters in this FLoRa-based simulation that had an influence on the network's performance. It was challenging to assess network performance under pressure since the user may change these factors, which had a big impact on network capacity. LoRaWAN network performance in application scenarios can be most reliably achieved through experimentation and the evaluation of significant parameters (Bor & Roedig, 2017).For the initial topology proposed, it was possible to increase the number of mobile nodes with the limitation of consuming the capacity and resources of the computer upon running the simulation. These conditions and the computing with four CPU and 8 GB RAM constrained the well performance. Our topology included five mobile nodes, three stationary gateways, a router, and a server, as depicted in Figure 4.

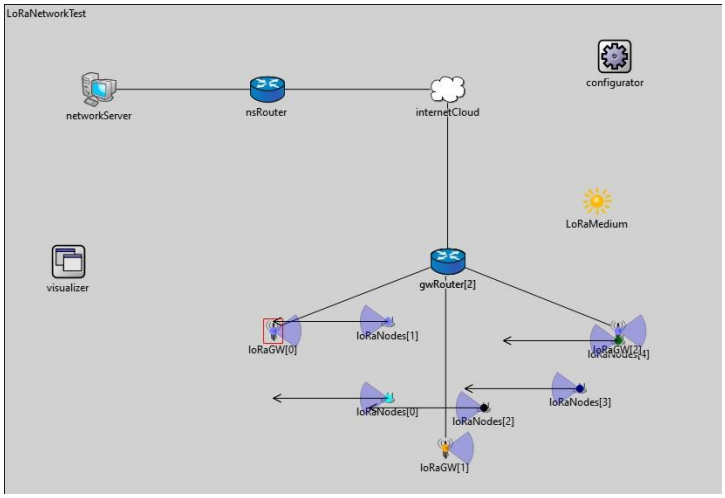


Figure 4. Topology with five mobile nodes

4.2. RSSI and distance relationship

FLoRa allowed the RSSI measurement to infer the distance between the gateway and the target by testing repetition. Before starting the position calculation process, we established a relationship between the distance from the gateways to the node and the RSSI value, i.e., the signal intensity received by the gateways. For LoRaWAN, these values fluctuated between -130 dB and -30 dB, in which -130 dB represents a very low intensity, indicating that the device was far away. Opposite, -30 dB represents strength intensity, meaning the device was close.

Experimentally, we underwent several simulations through the process depicted in Figure 5 to know the distance between the node and the gateway, obtaining the RSSI value to the gateway. The distance from the node was varied to calculate one more time the RSSI value. Figure 6 and Table 2 show the data obtained from the trials to establish the relationship between distance variation and RSSI based on this process.

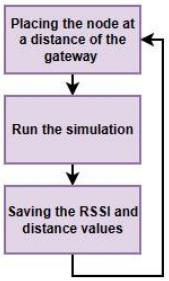


Figure 5. Iteration process to calculate RSSI vs distance variation

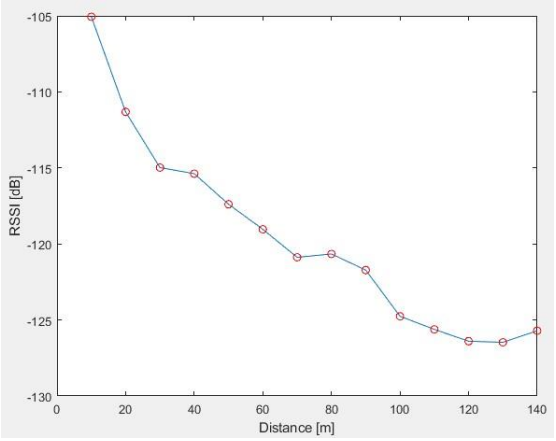


Figure 6. Relationship between RSSI and distance variation

4.3. Node position

The mobile node followed a circular path and frames were constantly conveyed to the gateways to obtain the RSSI corresponding to each. These values were displayed on the console and manually copied to verify the distance they correspond to using Table 2. Hence, we obtained the necessary data to solve the equation systems denoted in equations 1 through 3. Figure 7 shows a screenshot of this process, where green represents the node's circular trajectory, the red lines represent the frame-sending process pointing towards the gateways, and the console at the bottom displays the RSSI values of each gateway highlighted in yellow.

Table 2. RSSI obtained from the distance between the gateway and the mobile node

RSSI [dB]	Distance [m]
-105.06	10
-111.32	20
-114.98	30
-115.38	40
-117.39	50
-119.04	60
-120.88	70
-120.66	80
-121.72	90
-124.76	100
-125.62	110
-126.40	120
-126.47	130
-125.71	140

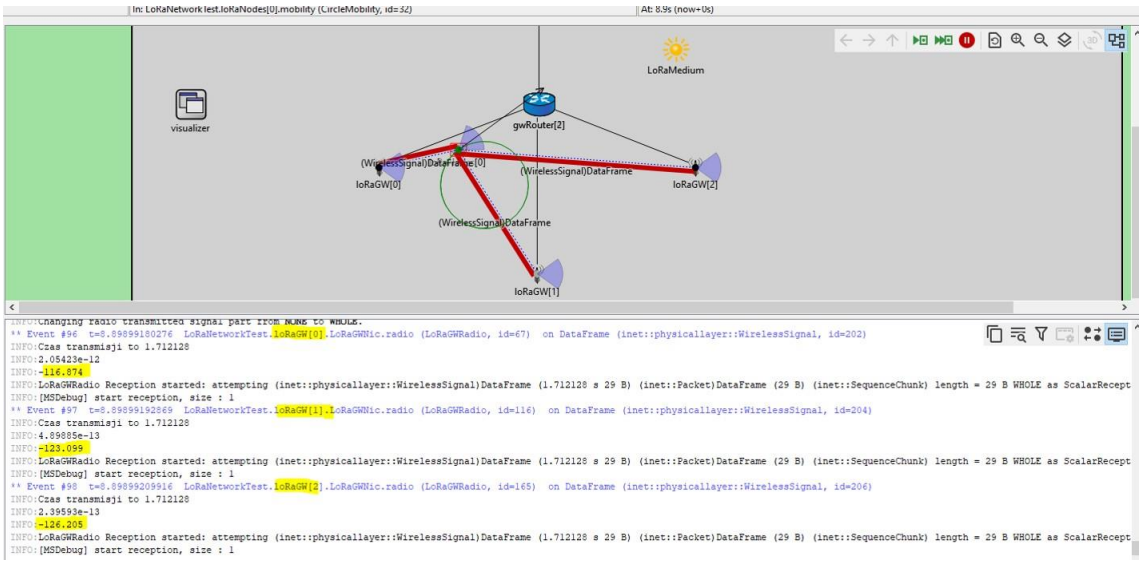


Figure 7. Node mobility and frame conveying process

We measured four node positions within the simulation to test that the power consumption and accuracy values were consistent while the nodes changed position. Table 3 contains the data of the four measurements we carried out in the three gateways, showing the information corresponding to the RSSI, distance to the node using the values of Table 2, and power consumption in milliwatts (mW). Figures 8 and 9 depict real position screenshots obtained through FLoRa and the trilateration results through Python command lines, respectively.

Table 3. Measurement values obtained in three gateways

Measurement	Gateway	RSSI [dB]	Distance [m]	Power [mW]
1	1	-111.84	20	2.05
	2	-121.42	30	0.49
	3	-127.67	130	0.24
2	1	-116.87	45	3.15
	2	-123.10	95	0.40
	3	-126.21	120	0.23
3	1	-116.62	45	2.18
	2	-117.33	50	1.85
	3	-120.53	70	0.89
4	1	-116.87	45	2.05
	2	-123.10	95	0.49
	3	-126.21	130	0.24

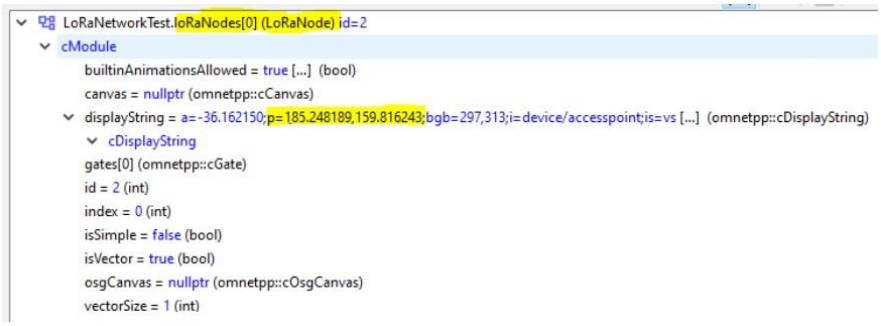


Figure 8. Screenshot of the real node position obtained in FLoRa

```
def findNode(x1,y1,r1,x2,y2,r2,x3,y3,r3):
    A = 2*x2-2*x1
    B = 2*y2-2*y1
    C = r1**2-r2**2-x1**2-x2**2-y1**2-y2**2
    D = 2*x3-2*x2
    E = 2*y3-2*y2
    F = r2**2-r3**2-x2**2-x3**2-y2**2-y3**2
    x = (C*E-F*B)/(E*A-B*D)
    y = (C*D-A*F)/(B*D-A*E)
    return x,y

#Apply trilateration algorithm for node location
x1=140
y1=170
r1=37
x2=230
y2=231
r2=75
x3=320
y3=170
r3=105
x,y = findNode(x1,y1,r1,x2,y2,r2,x3,y3,r3)

#Output node location / coordinates
print("Node location: ")
print(x,y)

#Shell output
#Node location: 203.17777  138.79508
#>
```

Figure 9. Pseudo code for the theoretical node location through trilateration

While running several tests, we achieved a lower difference between the real and theoretical (trilateration) positioning values. Table 4 regards the node position information calculated by trilateration $(\hat{x}, \hat{y})$, real calculation (x,y), and position errors in meters. In all of them, the power consumption was 25.12 mW. In most of the tests, we obtained an estimated difference of ±20 meters calculated through a straight line. Running more simulations can be recommendable, but the outlier values appear once every fifty or more runs. It is a rare event proper of the simulation framework, as outliers appear in the first run and cyclically when restarting the network. It could result from integrating the components and their synchronization with the network configuration, leading to an interpretation of an actual interaction behavior. Those values are not part of regular conditions, so we do not consider them for the calculations. Yet, the simulation complies with the expected power values in each gateway, so the further away the mobile node is located, the signal received by the gateway will become weaker.

Table 4. Positioning comparison

Measurement	$(\hat{x}, \hat{y})$	(x,y)	Error [m]
1	(203.17, 138.79)	(185.24, 159.81)	27.62
2	(195.63, 127.45)	(191.48, 156.50)	29.34
3	(222.01, 141.99)	(209.84, 160.02)	21.75
4	(188.68, 137.69)	(185.20, 159.85)	22.43

5. Conclusions

The integration of OMNeT++ and FLoRa allowed us to calculate precise node positioning, either at mobility or stationary conditions through the simulation performance of multiple nodes. Our proposal was carried out using an open-source software-oriented methodology, wherein the findings were comparable to those of previous studies using real devices under constrained circumstances in accordance with established settings. The benefits of our scheme are that OMNeT++ works based on open-source characteristics, supporting modification and distribution for educational or nonprofit reasons, and FLoRa has a public license to modify and distribute source codes. Therefore, it was possible to use the simulation platform as a convenient method for the development of new applications and tools to explore different features related to low-power technologies.

The topology with five mobile nodes supported geopositioning applications since it adhered to the trilateration technique, as the mobile nodes were within the coverage area of all three gateways at the same time. Similarly, we set up the parameters of the mobile nodes to keep them within the coverage radius of the three gateways. Other configurations can be set up based on the network's purpose. For example, if the user requires a network with greater coverage, the coordinates of the gateways that are the furthest apart should be determined. Similarly, another mobility module can be chosen for the nodes, granted that they are all within the coverage of the three gateways. We suggest modeling the desired parameters according to the final network application.

Because of the steps required to obtain reliable data, it took considerable time to determine the relationship between the RSSI and the distance between the gateway and the node. To get a more precise relationship between the distance and RSSI, the nodes experienced shorter positioning adjustments. It will consequently take longer to obtain the relationship values if greater precision is required. Additionally, we performed the positioning calculation procedure manually, which may cause a delay if the number of network nodes and configuration variables increase or get complex. If additional components are needed for simulation or real-device settings, further stages may focus on automating scripts.

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