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Computer modelling of LoRa network parameters using the FLoRa simulator

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Abstract. The purpose of this study was to investigate and compare the results of calculating the parameters of the LoRa network obtained by computer modelling with the results of experimental measurements. To fulfil this purpose, the methods of computer modelling of signal loss were used. Specifically, the study described a modification of the FLoRa simulator to estimate signal losses during propagation, perform computer simulations in FLoRa, and compare the findings obtained with the data obtained during the experiment. In addition, the RSSI values obtained in the simulation were compared with the experimental values. The functionality of the FLoRa software simulator was extended by adding signal power loss values to the simulation results table. Using the FLoRa software, the study simulated the signal power loss along the propagation path at frequencies of 433 MHz, 868 MHz, and 2.4 GHz. A comparative analysis revealed that the simulation results for different spreading factors and different signal frequencies correspond to the experimental data. It was found that the received signal power values are represented in the software as RSSI values. The signal power at the input does not correspond to the RSSI values and depends on the concrete type of receiver chip, and therefore the RSSI calculation methodology should be adjusted. It was confirmed that the results table should display both the signal strength at the receiver input and the RSSI value. To improve the accuracy of the FLoRa computer model, specifically, the calculation of RSSI values, it was proposed to consider the specific features of measuring these values by different types of LoRa receiver chips. The obtained findings can be used to improve the accuracy of modelling and, accordingly, the quality of designing networks based on LoRa technology

Keywords: Long Range; computer simulators; Framework for LoRa; Received Signal Strength Indicator; signal power loss; distribution factor; simulation parameters

Introduction

LoRa (Long Range) technology is widely used in modern sensor networks to ensure reliable communication between nodes. The advantages of this technology are long data transmission distances, high noise immunity, and minimal power consumption. With the rapid growth in the need to transmit data from many sensor nodes to remote servers, the relevance of optimising the parameters of LoRa networks is becoming critical.

Computer simulation provides powerful tools for modelling the behaviour of LoRa networks under various conditions and the ability to evaluate performance, identify potential problems, and test new solutions without the need to deploy expensive and time-consuming networks. D. Capriglione *et al.* (2012) found that by modelling different network scenarios, parameters such as signal propagation loss, interference level, data rate,

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received signal power, and energy consumption can be analysed in detail.

According to M.A.M. Almuhaya *et al.* (2022), one of the most widely used tools for modelling LoRa networks is simulation software. They provide researchers with the flexibility to configure network parameters and enable them to simulate a variety of scenarios that factor in the specifics of the network. This allows identifying potential problems, developing and testing optimisation strategies, which helps to improve the efficiency of the LoRa network in real-world conditions. In this regard, the relevance of computer modelling of LoRa network parameters, considering the features of the hardware, is undeniable.

Previous research has highlighted a series of key aspects related to LoRa transmission parameters. T. Rasic *et al.* (2021) investigated the effects of parameters such as the expansion ratio, bandwidth, and transmit power on communication efficiency and energy consumption using a FLoRa (Framework for LoRa) simulator. The study found that changing the distance between the node and the gateway considerably affects transmission stability and energy consumption. S. Francisco *et al.* (2021) proposed an improved LoRaSim (Long Range Simulator) model that improves the accuracy of reproducing real-world conditions through adaptive simulation parameters. O.A. Nahorniuk (2024) focused on methods for automatically determining the parameters of LoRa radio signals and focused on the peculiarities of modelling using MATLAB, which helped to improve the accuracy of measurements. However, there are still unresolved issues related to the reliability of simulation models compared to real experimental data, especially in scenarios where the distance between nodes changes substantially or where there is considerable interference.

S. Bertoldo *et al.* (2019) noted that the choice of a suitable signal propagation model is critical for accurately predicting LoRa network parameters. Their study demonstrated that the use of empirical models, such as Motley-Keenan or COST 231 Multi-Wall, can greatly improve the accuracy of predictions for sensor networks in indoor environments. This confirms the need for additional analysis and adaptation of simulators such as FLoRa to more accurately reproduce real-world operating conditions (FLoRa, n.d.).

M.G. Campos *et al.* (2024) noted the lack of representativeness of some simulator configurations when network parameters are varied. This points to the need for further research that validates simulation models in a wider range of conditions.

The purpose of this study was to analyse and compare the results of calculations of LoRa network characteristics obtained by computer simulation with the results of experimental studies.

To fulfil the purpose of the study, the following tasks were set:

1. Modify the FLoRa simulator software to display the values of signal propagation losses.
2. Conduct a computer simulation in FLoRa to obtain values of signal loss as a function of distance.
3. Compare the findings of the simulation with the data obtained from the visual experiment and the RSSI (Received Signal Strength Indicator) values obtained from the simulation with the values obtained from the experimental measurements.

Materials and Methods

The study employed a computer modelling method that allows predicting the parameters of the LoRa network based on theoretical models and experimental data. The key method for estimating signal propagation losses was the Fris model, which is widely used for calculations in urban environments. This model captures the random effects of shadowing due to natural and artificial obstacles such as hills, trees, buildings, and is known as the ordinary shadowing model. The Fries model was chosen because it is suitable for estimating losses in densely populated and built-up areas, which are typical conditions for LoRa network deployments. The model parameters, such as γ and X_σ, were chosen considering the specifics of the LoRa network and the environment in which the experiments were conducted. Using the Fris model, the path loss as a function of the communication distance d can be described as follows (Rappaport, 1996):

$$L_{pl}(d) = L_{pl}(d_0) + 10\gamma\, log\left(\frac{d}{d_0}\right) + X_\sigma, \tag{1}$$

where $L_{pl}(d)$ is the path loss in dB; $L_{pl}(d_0)$ is the loss at the reference distance d_0, γ is the path loss exponent; $X_\sigma \sim N(0, \sigma^2)$ is the deviation of a normal distribution with zero mean; and σ^2 is the variance to account for shadowing.

Losses at a reference distance d_0 when signals propagate without obstacles between the transmitter and receiver are equal:

$$L_{pl}(d_0) = 20\, log_{10}\left(\frac{4\pi f d_0}{c}\right).$$

At the same time, the losses on the way to distribution can be written as follows:

$$L_{pl} = P_{tx} + G_{tx} + G_{rx} - P_{rx}, \tag{2}$$

where *Ptx* is the strength of the transmitted signal; *Gtx*, *Grx* are the antenna gains, *Prx* is the signal strength at the receiver input.

The signal power at the receiver input P_{rx}, can be expressed as follows:

$$P_{rx} = RSSI + K,$$

where K is the offset, which depends on the characteristics of the transceiver chip used, the frequency, and the chosen technology and its features (in this case, LoRa and SF), or

$$P_{rx} = P_{tx} + G_{tx} + G_{rx} - L_{pl}. \tag{3}$$

Therefore, signal losses along the way can be expressed in terms of RSSI:

$$L_{pl}(d) = P_{tx} + G_{tx} + G_{rx} - RSSI - K. \tag{4}$$

Thus, based on the RSSI values obtained experimentally or as a result of simulation, it is possible to estimate the level of network losses at different distances. The relationship between RSSI and losses, expressed through the K-factor, is unique to each type of LoRa chip and was investigated by Yu. Onykiienko *et al*. (2022).

This study used the FLoRa simulator based on the OMNeT++ platform. Running simulations using FLoRa helped to simulate various environments based on the data obtained and preserve the conditions of the experiment, which makes the simulation results comparable to real measurements.

The receivers and transmitters used in the experiment (Fig. 1) were designed according to the modern element base. For measurements at 433 MHz, the study used the LoRa Ra-02 transceiver developed by Shenzhen Ai-Thinker Technology Co., Ltd (China), based on the SX1278 chip manufactured by Semtech Corporation (USA). For measurements at 868 MHz, the sudy used the TTGO LORA32 868/915 Mhz ESP32 LoRa OLED module created by the LILYGO team (China), based on the SX1276 chip from the same company Semtech Corporation (USA). Measurements at 2.4 GHz were performed using the E28-2G4M12S module developed by Chengdu Ebyte Electronic Technology Co., Ltd (China), based on the SX1280 chip manufactured by Semtech Corporation (USA).

The transmitter settings were changed during measurements via the built-in Wi-Fi channel of the ESP32 microcontroller. The receiver settings were changed via the LoRa channel. All the antennas are omnidirectional and vertically polarised, which minimised signal loss and helped to evaluate the network parameters in real-world conditions where interference from multidirectional objects often occurs. The data was transmitted in packets of 100 units with a payload of ten bytes and a 12-character preamble at each distance. The received RSSI values of each packet were recorded in the receiver's memory for further analysis of the effect of the SF spreading factor, which was set to 7, 9, and 12, and the distance at 433 MHz, 868 MHz, and 2.4 GHz. The initial data for modelling and calculations are presented in Table 1.

Node parameters, such as transmitter power, receiver sensitivity, and other characteristics, are configured according to chip specifications. For simulations, FLoRa uses a class-based signal propagation model, namely LoRaLogNormalShadowing, which factors in the characteristics of urban buildings, including reflection, attenuation, and other factors. A series of simulations were performed for various scenarios that reproduced the experimental conditions (different distances, frequencies, and other parameters). Each simulation included a certain number of data transmissions between nodes to collect statistically significant results. Thus, by means of experimental measurements and computer simulations, data were obtained that allow estimating the level of losses in the signal transmission path based on RSSI for different distances.

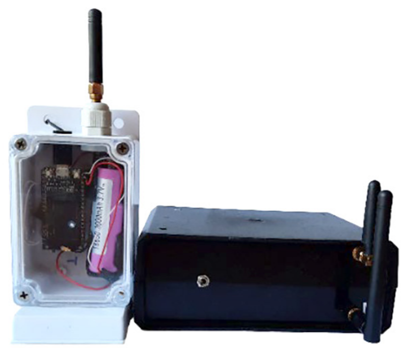

Figure 1*. LoRa modules used in the experiment (in the white case – a transmitter at a frequency of 868 MHz, in the black case – a transmitter at 433 MHz and 2.4 GHz)*
Source: *developed by the authors of this study*

Table 1*. Input data for modelling*

Frequency		433 MHz	868 MHz	2.4 GHz
σ		2.65		
γ		2.2		
Lpl(*d*0), dB		45.2	51.2	60.0
K	SF = 7	49	47	24
	SF = 9	54	50	25
	SF = 12	54	50	26
Frequency band, kHz		125	125	812.5
Coding rate		4/5	4/5	4/5
Output power, dBm		17	17	10
Antenna gain, dBi		2.5	2	3

Source: *developed by the authors of this study based on Yu. Onykiienko et al. (2022)*

Results

OMNeT++ provides the infrastructure and tools for running simulations. One of the fundamental features of this infrastructure is the architecture of components for simulation models. Models are assembled from many components called modules. Modules can be connected to each other using gateways and combined into composite modules. The depth of nesting of modules is not limited. Modules communicate through message passing, where messages can contain arbitrary complex data structures that can transmit messages along predefined paths through gateways and connections or directly to a destination; the latter is useful, e.g., for wireless simulations. Modules may have parameters that can be used to configure behaviour and/or to parameterise the model topology. The modules at the lowest level of the hierarchy are called simple modules, and they encapsulate the behaviour of the model. Simple modules are programmed in C++ and use the simulation library. OMNeT++ simulations can be run in a variety of user interfaces. Graphical user interfaces with animations are very useful for demonstration and debugging, while command line interfaces are best suited for batch execution.

FLoRa (n.d.) (Framework for LoRa) is a software library for end-to-end modelling of LoRa networks that provides support for the LoRa physical layer model, considering collisions and capture effects. It enables simulations with one or more gateways, provides accurate end-to-end modelling of the transport network, and provides statistics on network energy consumption. FLoRa is based on the INET framework, which is an open-source set of OMNeT++ models for wired, wireless, and mobile networks. The OMNeT++ environment and simulator allows creating LoRa networks with LoRa node, gateway, and network server modules. The parameters of the system elements are set in the initial simulation settings file. Figure 2 shows a fragment of the LoRa network simulation window.

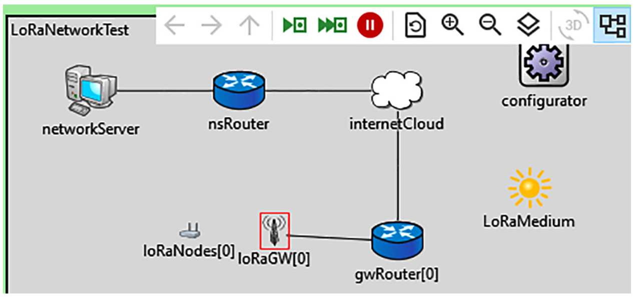

***Figure 2**. FLoRa simulation window*
***Source:** developed by the authors of this study*

The FLoRa package has all the necessary elements and their graphical representation to simulate both the network and server parts of the system, namely:

- A graphical representation in the LoRaNetworkTest plane of the network server (networkServer), router (nsRouter), network cloud (internetCloud), gateway (gwRouter), and LoRa node module (loRaGW – transmitter, loRaNodes – receiver);
- The duration of the simulation process is determined by the value set in the initialisation file. The results of the simulation are recorded in the results.anf file, which has the form of a table;
- Two signal propagation models LoRaHataOkumura and LoRaLogNormalShadowing can be used in the simulation;
- The simulation results, as well as the input data of the simulation, are entered into the table (Fig. 3). The parameters Vector of RSSI per node (RSSI value) and Vector of Pass Loss per node (loss value) are used to estimate the signal loss depending on the distance.

Browse Data

Here you can see all data that come from the files specified in the Inputs page.

All (4 005 / 4 005) | Parameters (2 576 / 2 576) | Scalars (1 074 / 1 074) | Histograms (90 / 90) | Vectors (265 / 265)

experiment filter | measurement filter | replication f | module filter

Experiment	Measurem...	Re...	Module	Name	Count	Mean	StdDev	Variance
General	$0="avg"	#0	LoRaNetworkTest.networkServer.eth[0].q	queueBitLength:vector	84	0 b	0 b	0 b²
General	$0="avg"	#0	LoRaNetworkTest.networkServer.eth[0].m	txPk:vector(packetBytes)	84	64	0	0
General	$0="avg"	#0	LoRaNetworkTest.nsRouter.eth[0].mac	rxPkOk:vector(packetBytes)	84	64	0	0
General	$0="avg"	#0	LoRaNetworkTest.nsRouter.eth[0].mac	passedUpPk:vector(packetBytes)	84	64	0	0
General	$0="avg"	#0	LoRaNetworkTest.nsRouter.ethernet	decapPk:vector(packetBytes)	84	46	0	0
General	$0="avg"	#0	LoRaNetworkTest.networkServer.udp	packetReceived:vector(packetBytes)	88	35	0	0
General	$0="avg"	#0	LoRaNetworkTest.networkServer.app[0]	Vector of SNIR per node	89	195.282367	182.871582	33,442.015409
General	$0="avg"	#0	LoRaNetworkTest.networkServer.app[0]	Vector of RSSI per node	89	-108.414612	3.452556	11.920146
General	$0="avg"	#0	LoRaNetworkTest.networkServer.app[0]	Vector of Pass Loss per node	89	129.414612	3.452556	11.920146
General	$0="avg"	#0	LoRaNetworkTest.loRaNodes[0].LoRaNic.	receptionState:vector	352	0.534091	0.563846	0.317923
General	$0="avg"	#0	LoRaNetworkTest.networkServer.app[0]	Received Sequence number	88	43.500000	25.547342	652.666667
General	$0="avg"	#0	LoRaNetworkTest.networkServer.app[0]	Calculated SNRmargin in ADR	4	192.664751	30.083020	904.988117
General	$0="avg"	#0	LoRaNetworkTest.networkServer.udp	packetSent:vector(packetBytes)	4	24	0	0
General	$0="avg"	#0	LoRaNetworkTest.nsRouter.ppp[0].queue	incomingPacketLengths:vector	4	352 b	0 b	0 b²
General	$0="avg"	#0	LoRaNetworkTest.nsRouter.ppp[0].queue	incomingDataRate:vector	864000	0.016296 bps	7.573821 bps	57.362764 bps²
General	$0="avg"	#0	LoRaNetworkTest.nsRouter.ppp[0].queue	queueingTime:vector	4	0 s	0 s	0 s²
General	$0="avg"	#0	LoRaNetworkTest.nsRouter.ppp[0].queue	outgoingPacketLengths:vector	4	352 b	0 b	0 b²

***Figure 3**. A fragment of the modelling results table with the output of signal loss values along the propagation path*
***Source:** developed by the authors of this study*

The FLoRa simulator calculates signal propagation losses but does not display them in a table with the results. In many cases, when designing a network, it is more convenient to use the loss values. Therefore, the program code has been modified, and the obtained values are displayed in the table after the RSSI values.

In Figure 4, the curves showing the dependence of signal loss on distance, different SFs, and frequency are modelled using formula (1) and calculated from experimental data using formula (4). The curve L, which shows the total signal loss with distance, is obtained as a result of modelling. The *min* and *max* curves indicate the minimum and maximum values of signal loss obtained during the simulation. The other curves, SF7, SF9, and SF12, respectively, represent the results of path loss calculations using formula (4), where the experimentally obtained RSSI and K values were applied.

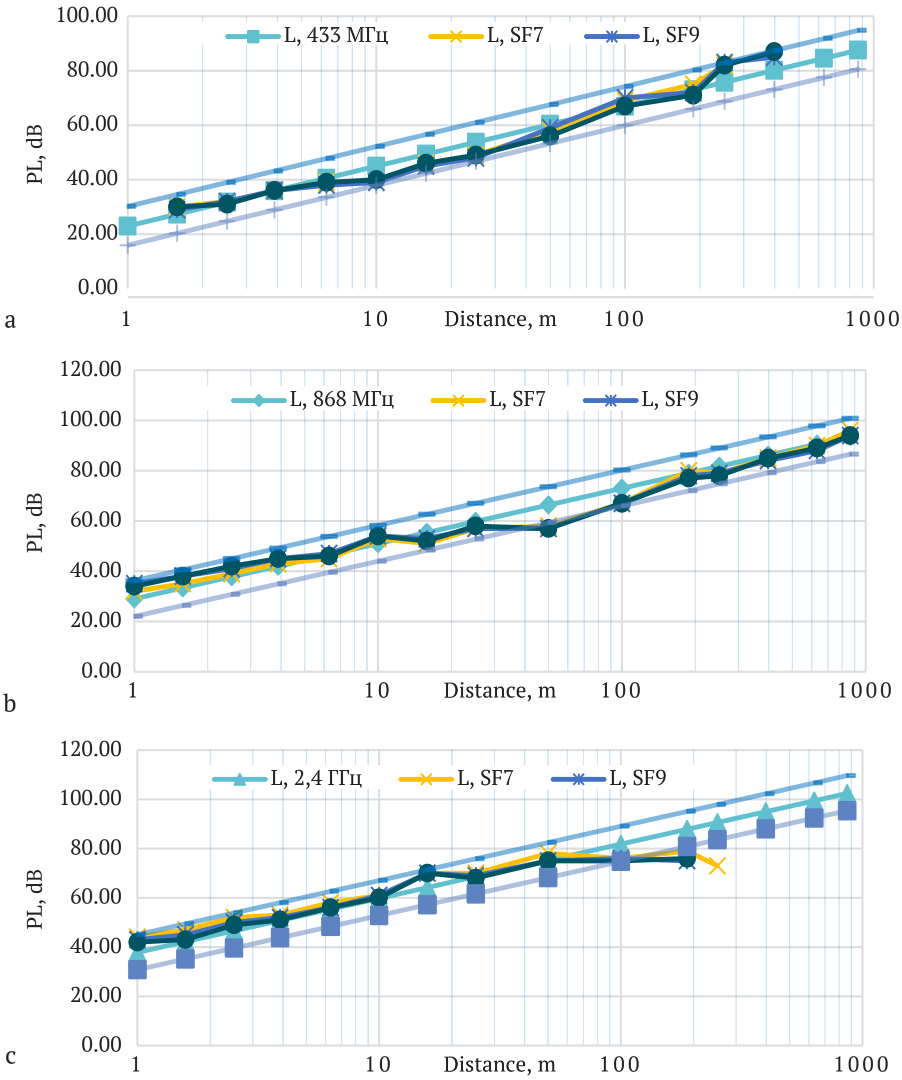

***Figure 4**. Dependence of signal loss at different frequencies on distance and distribution factor*
***Note:** a – 433 MHz, b – 868 MHz, c – 2.4 GHz*
***Source:** developed by the authors of this study*

The simulation and calculation results for the 433 MHz frequency are presented in Figure 4a. Clearly, the signal propagation loss obtained from calculations based on experimental data is within the maximum and minimum values obtained during simulation. The graphs show that the installed power and the selected antenna limit the range in the 433 MHz band to about 400 m. During reception at longer distances, a considerable increase in the number of errors was observed.

The graph for the 868 MHz frequency (Fig. 4b) shows that the signal loss obtained experimentally is within the range of theoretical calculations at most distances. Notably, at a distance of 50 metres, an additional signal reflection was observed during the experiment, and therefore the loss value at this point is lower than at the neighbouring ones. As a result, the theoretical models can be adjusted and improved based on real data to increase the accuracy of predictions and improve network planning processes.

Figure 4c shows signal loss versus distance at 2.4 GHz. The graphs show that the range in the 2.4 GHz band reaches approximately 250 m. At this point, reception errors became noticeable, which led to a considerable difference in the RSSI value calculated by formula (4) compared to neighbouring points. Achieving the specified distance is possible only if the distribution coefficient SF = 7 is used. For values of the spreading factor, such as SF = 9 and SF = 12, the maximum range in the 2.4 GHz band does not exceed 160 m. This confirms that lower SF values provide the maximum communication range of LoRa technology and increase interference immunity at analogous values of channel bandwidth and coding rate.

To estimate the signal power loss as a function of distance, the FLoRa software uses RSSI values for each endpoint. Considering that for LoRa networks, RSSI values depend on both the type of transceivers used and the SF distribution factor, the present study evaluated the consideration of these factors when performing calculations in the FLoRa simulator. Figure 5 presents the results of comparing the RSSI values obtained in the experiment conducted by Yu. Onykiienko *et al*. (2022) and those calculated in the FLoRa simulator as a function of distance at 868 MHz for different values of the SF distribution factor. Also presented in Figure 5 is the dependence of the signal power P_{rx} at the receiver input on the distance, calculated using formula (3).

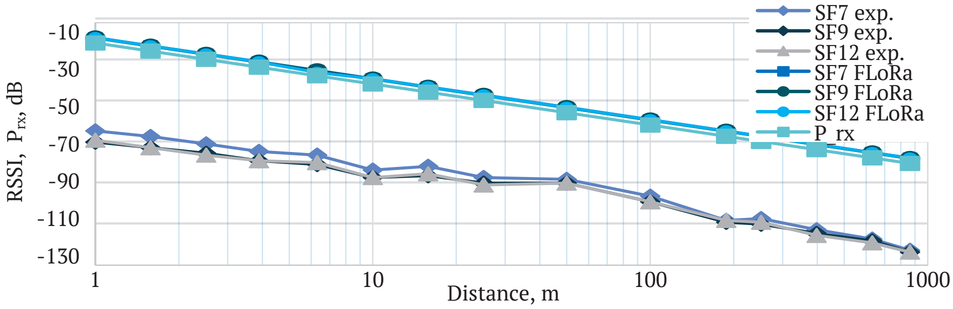

***Figure 5**. RSSI values obtained experimentally and in the FLoRa simulator at 868 MHz for different SFs at different distances and input power values P_{rx}*

***Source:** developed by the authors of this study*

Figure 5 shows that the RSSI values calculated in the FLoRa simulator with the parameter settings listed in Table 1 are significantly different from those obtained in the experiment. There is also no effect of the SF distribution factor. On the other hand, the simulation results almost coincide with the input power levels for the endpoint calculated by formula (3). Thus, in FLoRa, the received signal power values are represented as RSSI values. This approach is not entirely correct, since RSSI values depend on the concrete type of receiver chip. Therefore, the method of calculating RSSI in FLoRa should be adjusted. It would also be advisable to display both the signal value at the receiver input and the RSSI value in the results table.

Discussion

The findings of this study confirmed the significance of choosing the right spreading factor (SF) in LoRa networks to ensure the best performance. This is in line with the findings of S. Mnguni *et al*. (2021), who demonstrated that lower SF values (e.g., SF7) provided lower power consumption and faster data transmission, but could cause more packet collisions due to channel congestion. In the study, a modified version of the FLoRa simulator also showed high accuracy in assessing the impact of SF on signal loss and energy performance. Furthermore, this study expanded the FLoRa functionality by adding signal power loss modelling for different frequencies (433 MHz, 868 MHz, and 2.4 GHz). This helped to compare the simulation findings with experimental data and confirm that the choice of parameters, such as SF and transmit power, greatly affects network performance, including power consumption, latency, and throughput. However, the study found that the RSSI values presented in FLoRa need to be adjusted to consider the hardware characteristics of the receivers. This complemented the findings of S. Mnguni *et al*. (2021), indicating the need to further adapt the model to more accurately estimate the physical parameters of the network. The findings revealed the significance of optimising the spreading factors (SF) to ensure a balance between energy consumption, reliability, and transmission range in LoRa networks. It is also consistent with the findings of C. Bouras *et al*. (2021), who demonstrated that the use of machine learning can significantly improve energy efficiency and transmission reliability in LoRa networks through adaptive SF selection. In contrast to the approach of the researchers, the present study focused on modelling signal loss and estimating RSSI parameters using a modified version of FLoRa. At the same time, the findings confirmed that SF plays a critical role in network performance, especially in the context of multifactorial influences such as signal frequency, transmission medium, and distance to the gateway. C. Bouras *et al*. (2021) also pointed to the promise of integrating machine learning into simulators such as FLoRa for automated parameter tuning.

G. Premsankar *et al*. (2020), who used linear programming to find the optimum SF and TP parameters in dense urban networks, achieved an increase in the delivery ratio of up to 8% compared to previous algorithms and ensured a fair distribution of radio resources between nodes.

In contrast to the methodology of G. Premsankar *et al*. (2020), which focused on optimising real networks by modelling spatial configurations and the mutual influence of nodes, the present study is aimed at simulating the analysis of influence factors such as signal loss and RSSI values using the FLoRa tool. Nevertheless, the key findings of the researchers can be integrated into further research, specifically to improve ADR algorithms that have limitations in terms of their setup time. Furthermore, the approach demonstrated that the use of optimisation tools such as linear programming can be integrated with simulation platforms to enable rapid testing of different network configuration scenarios. This opens the prospect for future research on dynamic optimisation of LoRa parameters, which can increase the adaptability and efficiency of FLoRa.

At the same time, R. Serati *et al*. (2022) proposed a new ADR-Lite algorithm that optimises the settings of transmission parameters such as SF, TP, CF, and CR to achieve prominent flexibility and performance even in mobile environments. Unlike standard ADR, the ADR-Lite algorithm operates independently of received packet history, using a binary search to determine the optimum transmission parameters. This substantially reduces computational complexity, which is critical for the scalability of IoT networks. Simulations showed that in a mobile environment with high channel noise, ADR-Lite achieved a 2.8 times improvement in packet delivery ratio (PDR) compared to standard ADR and outperformed other algorithms by 35%. The present study highlighted the significance of including additional transmission parameters such as CF and CR in the optimisation process, which is also relevant for extending the functionality of the FLoRa simulator. The lack of dependence on the previous transmission history opens the prospect of integrating ADR-Lite into scenarios with dynamically changing channel conditions. Thus, the approach proposed by R. Serati *et al*. (2022) can form the basis for further research, including the use of machine learning to find the best transmission parameters without reducing PDR.

A considerable contribution to the understanding of LoRa technology was made by M.A. Kamal *et al*. (2023), which offered a detailed analysis of LoRa specifications, implementation history, simulation tools, as well as the principal technical and operational challenges. The researchers highlighted the key advantages of LoRa, such as wide range, low power consumption, and the availability of the technology due to the use of unlicensed frequencies. Among the technical challenges outlined in the study, special attention was paid to connection management, resource allocation, ensuring stable communication, and security in LoRa networks. Particularly interesting was the discussion of parameters that affect network performance, such as spreading factor (SF), bandwidth (BW), and bitrate calculation. The researchers presented a formula for determining the data rate depending on the selected parameters, which is useful for simulation experiments. The study also highlighted that despite the wide range of solutions, some issues are still unresolved. The discussion of simulation tools also provided a useful context for extending the functionality of FLoRa. The inclusion of new parameters, such as the effects of network topology or environmental changes, can substantially improve modelling accuracy and make simulations more realistic.

A.I. Griva *et al.* (2023) presented a comparative analysis of the performance of LoRa networks in rural, urban environments, and a car park scenario. The researchers used the OMNeT++ simulation environment with the open-source FLoRa framework. In rural areas, an increase in node density significantly degraded network performance, which was less noticeable in urban scenarios due to the better location of gateways and other infrastructure features. It was also found that increasing the expansion factor (SF) from SF 11 to SF 12 increased energy consumption by 50.76%. It was also emphasised that optimisation of parameters such as antenna height, transmit power, and number of gateways is a vital factor for efficient deployment of LoRa networks. Popular signal fading models, such as Okumura-Hata and Oulu, were used for modelling, which helped to evaluate the network performance in various conditions. The findings revealed that the correct choice of the signal fading model and technical parameters greatly affects the quality of communication and energy efficiency of the network. The researchers also emphasise the necessity of experimental studies to confirm the findings.

R.P. Centelles *et al*. (2024) considered a new Distance-Vector Routing Protocol (DV RP) for LoRa Mesh networks. The proposed approach aimed to extend the capabilities of the conventional LoRaWAN star topology by using a more flexible mesh topology. The principal innovation was the Time on Air (ToA) metric, which accommodated the possibility of using different spanning factors (SFs) for efficient routing in networks with heterogeneous topologies. The advantages of using multi-SF included the use of different SFs, while allowing for optimised data transmission, especially in cases of high loads, improving network performance. The protocol is optimised for limited node computing resources, making it suitable for low-power devices. In simulations using FLoRa based on OMNeT++, the study demonstrated better packet delivery ratio (PDR), goodput, and latency compared to other known routing strategies in heterogeneous topologies. This study is a valuable contribution to the development of LoRa Mesh networks by showing the potential of multi-SF routing to solve real-world problems in challenging environments. In the future, the researchers plan to implement the developed protocol on real devices for field trials, which emphasises the practical orientation of the study. The findings revealed that the correct choice of the signal fading model and technical parameters considerably affects the quality of communication and energy efficiency of the network.

Y. Sarr *et al*. (2019) proposed the deployment of a street lighting control system based on LoRaWAN technology for smart cities. The system, which operates on the principle of 'smart lighting', allows solar lights to dynamically adjust the level of illumination depending on environmental conditions and the state of energy supply. The study showed that the use of a single gateway causes a large loss of packets due to collisions, which confirmed the need for multiple gateways to improve network performance. The simulation results showed that multiple gateways considerably reduce packet loss and collisions (up to 20%), which indicates the value of network scalability for the best results.

E.F. Silva *et al.* (2023) proposed the SlidingChange mechanism, which helps to dynamically adjust these parameters depending on the network conditions and provides an opportunity to reduce the number of configuration changes in the network. This approach, compared to other methods such as InstantChange and LR-ADR, revealed a significant improvement in Signal-to-Noise Ratio (SNR) and Bit Error Rate (BER). At the same time, by using a sliding window to smooth out short-term changes, it reduced the need for frequent network reboots. Overall, the use of techniques such as SlidingChange can greatly improve the efficiency of a LoRa network by reducing the number of frequent frequency and configuration changes, which reduces energy consumption and increases network stability. This is especially significant for large IoT networks where many devices need to communicate with the network with minimal energy consumption and high data reliability.

G. Yascaribay *et al*. (2022) focused on evaluating the effectiveness of communication systems for IoT in agriculture, specifically the use of LoRaWAN. In this study, based on simulations using Omnet++ and the FLoRa library, the performance of LoRaWAN in rural areas was evaluated using the example of Ecuador. The researchers showed that by using two gateways and activating Adaptive Data Rate (ADR) technology, the packet delivery ratio can be considerably increased without increasing the power consumption of network nodes. These findings demonstrated the potential of LoRaWAN to solve the problem of providing reliable communication in an agricultural environment, where the distance between nodes can reach great values and energy-saving features are vital for the long-term operation of devices. Importantly, the study also highlighted the need to develop additional mechanisms to improve network scalability, such as the introduction of multiple communication channels to reduce packet collisions, which is a prominent issue when there are a considerable number of nodes in the network. Such aspects still require further study, as existing protocols do not provide optimised traffic management in situations where the number of gateways and nodes increases significantly.

Conclusions

The analysis of the simulation results using FLoRa software revealed that the obtained results of modelling the signal loss along the propagation path correspond to the experimental data. For frequencies of 433 MHz, 868 MHz, and 2.4 GHz, the signal losses obtained in the simulation were within the experimental values, which confirmed the high accuracy of the simulation model for predicting signal propagation losses. Specifically, this confirmed that the model can correctly account for various factors that affect the nature of signal propagation in real-world conditions, including environmental changes, obstructions, and interference. Particular attention should also be paid to the consideration of various propagation factors (SF) and different signal frequencies, which were also accurately modelled, helping to assess the effects of these parameters on signal loss.

The comparison of simulation and experimental data confirmed that the computer modelling methods employed in this study are effective in predicting the characteristics of LoRa networks. The results of simulations performed using the FLoRa software revealed high agreement with experimental measurements within the permissible errors, which suggests the accuracy of the model for predicting signal loss and other parameters such as delay and interference. This opens new opportunities for the development of adaptive models that accommodate both hardware and environmental factors when selecting SF. Thus, the use of machine learning can be a logical step in improving FLoRa to predict network parameters more accurately.

The FLoRa software simulator proved to be a powerful tool for modelling systems based on LoRaWAN technology. The openness of the software source code helped to adapt the simulator to the concrete conditions and needs of various studies, considering the environment.

In the future, a valuable area is to improve the FLoRa simulation programme to more accurately calculate the RSSI output values, specifically by considering additional factors such as hardware features of the system implementation and changes in the propagation coefficients (SF) during the simulation.

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Conflict of Interest

None.

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Комп'ютерне моделювання параметрів мережі LoRa з використанням симулятора FLoRa

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Анотація. Метою статті було дослідження та порівняння результатів обчислень параметрів мережі LoRa, отриманих за допомогою комп'ютерного моделювання, з результатами експериментальних вимірювань. Для досягнення мети було використано методи комп'ютерного моделювання втрат сигналу. Зокрема, у статті описано модифікацію симулятора FLoRa для оцінки втрат сигналу під час його поширення, виконання комп'ютерних симуляцій у FLoRa та порівняння отриманих результатів з даними, здобутими в ході експерименту. Також проведено порівняння значень RSSI, отриманих у процесі симуляції, з експериментальними значеннями. Розширено функціональні можливості програмного симулятора FLoRa шляхом додавання значень втрат потужності сигналу до таблиці результатів симуляції. З використанням програми FLoRa виконано симуляцію втрат потужності сигналу на шляху поширення на частотах 433 МГц, 868 МГц та 2,4 ГГц. Порівняльний аналіз показав, що результати симуляції для різних коефіцієнтів розподілення) та різних частот сигналу відповідають експериментальним даним. Встановлено, що в програмі значення потужності отриманого сигналу представлені як значення RSSI. Потужність сигналу на вході не відповідає значенням RSSI і залежить від конкретного типу мікросхеми приймача, тому методика розрахунку RSSI має бути скорегована. Підтверджено, що було б доцільно виводити в таблицю результатів як значення сигналу на вході приймача, так і значення RSSI. Для підвищення точності комп'ютерної моделі FLoRa, зокрема обчислення значень RSSI, запропоновано враховувати особливості вимірювання цих значень різними типами мікросхем приймачів LoRa. Отримані результати можуть бути використані для підвищення точності моделювання і відповідно якості проектування мереж на основі технології LoRa

Ключові слова: Long Range; комп'ютерні симулятори; Framework for LoRa; Received Signal Strength Indicator; втрати потужності сигналу; коефіцієнт розподілення; параметри симуляції