IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Ingénierie des Systèmes d'Information
Vol. 31, No. 10, October, 2026, pp. 3253-3271
Journal homepage: http://iieta.org/journals/isi

An Optimized K-Means-Based Approach for LoRaWAN Gateway Placement in Forest Fire Monitoring: A Performance Evaluation Using NS-3

Amira Sairi[1*], Said Labed[1], Akram Kout[2], Badreddine Miles[1], El-Bay Bourennane[3]

[1] MISC Laboratory, University of Abdelhamid Mehri Constantine 2, Constantine 25000, Algeria
[2] MISC Laboratory, Salah Boubnider Constantine 3 University, Constantine 25000, Algeria
[3] ImViA Laboratory, University of Bourgogne Europe, Dijon 21078, France

Corresponding Author Email: amira.sairi@univ-constantine2.dz

Copyright: ©2026 The authors. This article is published by IIETA and is licensed under the CC BY 4.0 license (http://creativecommons.org/licenses/by/4.0/).

https://doi.org/10.18280/isi.311002

Received: 29 June 2026
Revised: 13 October 2026
Accepted: 21 October 2026
Available online: 31 October 2026

Keywords:
Long Range Wide Area Network, gateway placement, K-Means clustering, forest-fire monitoring, Packet Delivery Ratio, energy consumption

ABSTRACT

Reliable communication is essential for forest-fire monitoring over large, remote areas, where the placement of gateways can affect the performance of low-power wide-area sensor networks. This study evaluates a K-Means-based method for locating Long Range Wide Area Network (LoRaWAN) gateways in a modeled forest environment. The Chettaba Forest in Algeria is used to define the geographical study area, which is converted into an equivalent circular simulation region. Sensor-node coordinates are generated within this region, and K-Means clustering is applied to determine gateway placement optimization from the spatial distribution of the nodes. The resulting configurations are evaluated using NS-3.45 for networks of 10–2,000 nodes, one to three gateways, and transmission intervals of 60–300 s. Performance is assessed in terms of Packet Delivery Ratio (PDR), average energy consumption per node, and sensor-area coverage. In the 2,000-node scenario with a 60-s transmission interval, the two-gateway K-Means deployment achieves a PDR of 0.676, compared with 0.512 under random gateway placement, corresponding to a relative improvement of 32.0%. Average energy consumption per node is reduced by 57.6% under the same conditions. Separately, the estimated sensor-area coverage reaches 77.84% with 2,000 nodes. The results indicate that clustering-based gateway placement can improve simulated communication reliability and energy efficiency, particularly under high network loads. As the evaluation is simulation-based and uses a modeled representation of the forest, field measurements are still required to establish performance under actual propagation and deployment conditions.

1. INTRODUCTION

Forests are among the most important natural resources for human well-being and for maintaining the ecological balance of the Earth. However, forest fires have become a major environmental and socioeconomic concern worldwide. They cause extensive damage to vegetation and wildlife while threatening nearby populations and infrastructure. Prolonged droughts, rising temperatures, and human activities have contributed to the increasing occurrence and severity of wildfires. In Mediterranean countries such as Algeria, forest fires are particularly frequent during the dry season and can have significant impacts on biodiversity and human settlements. Consequently, effective monitoring and early detection are essential for reducing the potential impacts of wildfire events [1-3].

Traditional forest fire detection systems, including satellite imaging, camera-based monitoring, and human observation towers, face several limitations related to detection time, operational requirements, and environmental conditions. Satellite-based systems can cover large areas but may have limited capability to detect small ignition points at an early stage because of spatial and temporal resolution constraints. Camera-based systems, in turn, require an adequate power supply and line of sight and can be affected by fog, wind, smoke, and other environmental conditions. These limitations have encouraged the development of more autonomous and distributed technologies for forest fire prevention and early detection [4, 5].

In this context, the Internet of Things (IoT) has emerged as a promising technological paradigm for environmental monitoring. IoT-based systems enable continuous data collection from geographically distributed sensing nodes through the integration of sensors, processing units, and wireless communication technologies. In forest environments, however, the effectiveness of an IoT monitoring system depends strongly on the communication technology used to connect sensor nodes over large and potentially inaccessible areas. Such a technology should provide long-range communication while maintaining low power consumption and reliable connectivity [3].

Low-Power Wide-Area Networks (LPWANs) have emerged as promising communication technologies for wide-area and remote monitoring applications [6]. They are designed to support long-range communication with low power consumption, making them suitable for battery-

operated sensor nodes deployed in difficult-to-access environments. These characteristics have encouraged their use in environmental monitoring applications, including forest fire surveillance [7, 8].

Sigfox, Long Range (LoRa)/Long Range Wide Area Network (LoRaWAN), and Narrowband IoT (NB-IoT) are among the widely used LPWAN technologies. LoRaWAN is particularly suitable for large-scale sensing applications because it supports long-range communication, bidirectional data transmission, adaptive data rate (ADR), and end-to-end security mechanisms. In addition, LoRaWAN can be deployed using either private or public network infrastructures, providing flexibility for application-specific deployments [9]. These characteristics make LoRaWAN a suitable communication technology for the forest fire monitoring scenario considered in this study.

However, deploying a LoRaWAN-based sensor network over a forest environment requires careful gateway planning. The number and spatial placement of gateways affect the communication distances between sensor nodes and gateways and consequently influence network reliability, spatial coverage, and energy consumption. Therefore, determining suitable gateway locations is an important network-planning problem, particularly for large and geographically distributed forest monitoring areas.

Although K-Means clustering has been widely investigated for wireless sensor network (WSN) and LoRaWAN deployment problems, its application in this study is considered within a specific forest fire monitoring scenario. The proposed approach combines a geographic representation of a forest environment with K-Means-based spatial gateway placement and subsequent LoRaWAN network evaluation using NS-3.45.

The objective is not to introduce a new clustering algorithm, but to investigate the resulting gateway configurations within a forest-oriented LoRaWAN simulation framework and evaluate their communication performance, area coverage, and energy consumption.

The Chettaba Forest area in Constantine, northeastern Algeria, is considered as a geographical reference for constructing the simulation environment. Rather than representing an actual sensor deployment, the forest is modeled using geographic coordinates derived from the study area and transformed into the Universal Transverse Mercator (UTM) coordinate system. This representation provides a reproducible spatial environment for investigating LoRaWAN gateway placement and network performance. Remote sensing data, including Sentinel-2-derived Normalized Difference Vegetation Index (NDVI) and Landsat 8-derived land surface temperature (LST), are used to characterize the environmental and fire-risk conditions of the selected area. These data provide environmental context for the modeled study area but are not used as direct inputs to the K-Means gateway placement procedure.

The main objectives of this research are to: 1) create a reproducible geometric model of the forest region for large-scale IoT simulation. 2) apply the K-Means algorithm for gateway placement optimization based on the geographical distribution of sensor nodes. 3) simulate LoRaWAN communication behavior using NS-3.45 under different network configurations. 4) evaluate network performance using Packet Delivery Ratio (PDR), area coverage, and energy consumption. The main contributions of this paper are summarized as follows: 1) a reproducible geospatial simulation framework for evaluating LoRaWAN gateway placement in a modeled forest environment. 2) a K-Means-based LoRaWAN gateway placement optimization approach for forest fire monitoring applications. 3) a performance analysis based on PDR, energy consumption, and area coverage, including comparisons with non-optimized gateway deployment strategies.

The remainder of this paper is organized as follows: Section 2 presents the literature review and related work on IoT and LoRaWAN-based forest fire detection systems. Section 3 details the proposed methodology, including forest modeling, optimization, and simulation setup. Section 4 presents and analyzes the simulation results, Section 5 discusses the findings, and Section 6 concludes the paper and outlines future research directions.

2. BACKGROUND

2.1 Low-Power Wide-Area Network technology

The growing adoption of the IoT has created a strong demand for communication technologies that can interconnect a large number of devices while ensuring low energy consumption, wide coverage, and reduced costs. Traditional wireless technologies such as Wi-Fi, Bluetooth, and ZigBee are generally less suitable for wide-area and long-range applications because they are primarily designed for short-range communication and may involve higher energy requirements for extended-area deployments. LPWANs are a novel wireless connectivity paradigm designed to support large-scale Internet of Things deployments while addressing these requirements [10].

LPWAN technologies are based on several core characteristics. First, they facilitate communication over great distances, usually ranging from tens of kilometers in rural regions to several kilometers in crowded urban areas. Second, they enable very low energy consumption, allowing end devices to operate on small batteries for several years. Third, LPWANs typically provide low data rates, ranging from a few bits to a few kilobits per second, making them suitable for applications such as metering and environmental monitoring. Finally, these technologies offer high scalability and relatively low deployment costs, allowing large numbers of devices to be connected within a single network [11].

Several wireless solutions have been developed within the LPWAN category, each adopting different design approaches and deployment models. LoRa is a physical-layer technology based on Chirp Spread Spectrum (CSS) modulation, which provides robustness against interference and enables long-range communication. Building on this physical layer, LoRaWAN defines an open standard for the medium access and network layers and uses a star-of-stars topology in which gateways forward data packets to a network server. Thanks to its openness and flexibility, LoRaWAN has rapidly become one of the most popular LPWAN technologies for academic research and industrial deployment [12, 13].

Sigfox represents a contrasting approach, as it is a fully proprietary solution that relies on ultra-narrowband modulation. It is designed for low data throughput and low energy consumption but imposes limitations on message size and the number of daily transmissions. This makes Sigfox particularly attractive for simple and delay-tolerant applications, such as asset tracking or utility metering.

However, its lack of flexibility compared to open standards limits its broader applicability [10, 14].

NB-IoT, standardized by Third Generation Partnership Project (3GPP), is a cellular-based LPWAN technology that operates in licensed spectrum and relies on existing Long-Term Evolution (LTE) infrastructure. It provides reliable and secure communication with wide-area coverage, making it suitable for industrial and mission-critical IoT applications. Compared to unlicensed LPWAN solutions, NB-IoT achieves better scalability and ensures a higher quality of service, although these benefits come with increased deployment and operational costs [15].

Long-Term Evolution for Machine (LTE-M), also referred to as LTE Cat-M1, is a cellular-based LPWAN technology defined by 3GPP. In contrast to NB-IoT, it supports device mobility and voice services through Voice over LTE (VoLTE), while maintaining low energy consumption. With its higher data rates, LTE-M is particularly suitable for use cases such as wearable technologies, health applications, and intelligent transportation systems. Overall, it provides a compromise between energy efficiency and performance, making it well adapted to IoT scenarios that require both low power consumption and moderate throughput [16].

The four main LPWAN technologies, LoRaWAN, Sigfox, NB-IoT, and LTE-M, each have advantages but also certain limitations. Sigfox stands out for its very low energy consumption and simple connectivity; however, its strict restrictions on the size and number of messages transmitted limit its flexibility. NB-IoT and LTE-M, both standardized by 3GPP, offer high reliability and security through the use of licensed spectrum and existing cellular infrastructure. However, these advantages may involve higher deployment costs and energy consumption, which can limit their suitability for some large-scale, low-cost deployments. In comparison, LoRaWAN offers an attractive compromise between extended range, low power consumption, and cost efficiency. Furthermore, as an open standard supported by the LoRa Alliance, it supports both private and public network deployments, providing greater flexibility than proprietary approaches such as Sigfox [14].

Among the various LPWAN technologies, LoRaWAN is particularly well suited to environmental monitoring applications. It combines low energy consumption, long range, and low deployment costs, making it a viable solution for sensor networks deployed in large, hard-to-reach areas. This adaptability, combined with its robustness against interference and scalability, explains its growing use in environmental monitoring systems. Thus, for forest fire detection and prevention, LoRaWAN offers a combination of strategic advantages: extended sensor autonomy, coverage of large forest areas, and the possibility of deploying infrastructure at a lower cost, while ensuring reliable connectivity in remote environments [14, 17, 18].

2.2 Long Range and Long Range Wide Area Network

LoRa technology and its associated LoRaWAN protocol are currently among the most representative solutions for LPWAN networks. LoRa corresponds to the physical layer, developed by Semtech, and is based on CSS modulation, which provides robust, long-range communication with low energy consumption. It operates in unlicensed Industrial, Scientific and Medical (ISM) frequency bands, such as 433, 868, and 915 MHz, depending on the regional regulations. LoRa can provide communication over several kilometers in urban areas and up to 15–20 km under favorable rural conditions. Its spreading factor (SF), ranging from SF7 to SF12, provides a trade-off between data rate and communication range [13].

The LoRaWAN architecture is based on a star-of-stars topology, in which end devices communicate directly with one or more gateways. These gateways act as communication bridges by relaying messages to a centralized network server, usually connected to the Internet Protocol (IP) infrastructure via Ethernet, 3G/4G, or fiber optics. The network server plays a key role: it authenticates devices, verifies message integrity, and manages redundancy when the same packet is received by multiple gateways. The validated data is then transmitted to the application server, which acts as the interface between the LoRaWAN network and the end user's services or applications (e.g., environmental monitoring systems, smart agriculture, or predictive maintenance).

This architecture therefore separates three main entities: end devices, which measure environmental parameters or trigger actions; gateways, which collect radio packets transmitted via LoRa and forward them to the network server; and the network and application servers, which manage the network and process the collected data, respectively. Because of this organization, LoRaWAN can cover large geographical areas with a limited number of gateways while maintaining low energy consumption on the sensor side, making it an architecture suited to massive IoT deployments in both urban and rural environments [11]. To optimize network performance, LoRaWAN uses the ADR mechanism to adjust communication parameters, such as the SF and transmission power, based on radio link quality and network conditions.

In addition, the protocol supports three device classes. Class A devices open a reception window only after each transmission, resulting in low energy consumption. Class B introduces synchronized reception windows using beacons sent by gateways, providing a compromise between energy efficiency and responsiveness. Class C devices keep their receivers continuously active, providing low latency at the cost of higher energy consumption [9, 19]. This class hierarchy allows LoRaWAN to support a wide range of use cases, from battery-powered environmental sensors operating for several years to applications requiring near-real-time communication [14].

In the LoRaWAN protocol, two main categories of data messages can be transmitted between end devices and the network: confirmed and unconfirmed messages. Unconfirmed messages are sent by a device to a gateway without waiting for acknowledgment. They enable energy-efficient transmission and are suitable for applications where occasional data loss is acceptable, such as environmental telemetry and periodic measurements. Confirmed messages, on the other hand, require an acknowledgment from the network server. If an acknowledgment is not received, the end device retransmits the packet according to the retransmission procedure defined by the protocol. This mode of communication can provide greater reliability but may result in higher energy consumption and increased latency. These two message types provide a trade-off between energy efficiency and transmission reliability, allowing LoRaWAN to support applications with different communication requirements, including applications that can tolerate occasional data loss [12, 19].

2.3 K-Means clustering algorithm

Clustering is an unsupervised learning technique that automatically groups data into homogeneous sets called clusters without requiring prior labels. Elements within the same cluster share strong similarities, while those belonging to different clusters have notable differences [20]. This grouping is based on similarity or distance measures, such as Euclidean distance, which are used to determine the proximity between objects [21]. The clustering method typically consists of multiple steps: expressing the data in a multidimensional space, grouping by minimizing intra-cluster distance and maximizing inter-cluster distance, and assessing the quality of the groupings. Several clustering techniques are available, including K-Means and Density-Based Spatial Clustering of Applications with Noise (DBSCAN). K-Means defines centroids for the clusters and assigns each data point to the nearest centroid [21]. In contrast, DBSCAN identifies high-density regions separated by lower-density areas [22].

The resulting groupings can be evaluated using metrics such as the Silhouette Score, which assesses internal coherence and group separation [23]. This approach is widely used to highlight hidden structures in data and has a variety of applications, ranging from image segmentation to the optimization of IoT sensor networks [24], particularly for the placement of gateways in a LoRaWAN network [25]. The K-Means algorithm is one of the most popular partitioning methods in unsupervised learning. It aims to divide a dataset into k clusters while minimizing the intra-cluster variance. Given a dataset $X = \{x_1, x_2, \cdots, x_n\}$ in a d-dimensional space $\mathbb{R}^d$, each cluster C_j is represented by a centroid μ_j, defined as the mean of the points assigned to it.

The algorithm seeks to minimize the following cost function:

$$J = \sum_{j=1}^{k} \sum_{x_i \in C_j} \|x_i - \mu_j\|^2 \quad (1)$$

where, J corresponds to the sum of squared Euclidean distances between each data point x_i and its centroid μ_j. The algorithm proceeds iteratively in four main steps:

1) Initialization: Select k initial centroids randomly.

2) Assignment: Assign each point x_i to the cluster with the nearest centroid according to the Euclidean distance.

3) Update: Recompute the centroid of each cluster as the mean of the points assigned to it:

$$\mu_j = \frac{1}{|C_j|} \sum_{x_i \in C_j} x_i \quad (2)$$

4) Iteration: Repeat steps 2 and 3 until convergence, i.e., when centroids stabilize, or a maximum number of iterations is reached.

K-Means is widely appreciated for its simplicity, computational efficiency, and scalability on large datasets [20, 21].

However, it suffers from several limitations: it is sensitive to the choice of initial centroids, requires the number of clusters k to be defined a priori, and can converge to a local rather than a global minimum. Moreover, various K-Means variants have been developed, including parallel and distributed implementations as well as adaptive methods designed to handle large-scale and streaming datasets. A comprehensive review [26] highlights the wide range of K-Means variants, confirming its position as an essential and continuously evolving clustering method.

2.4 Related work

In recent years, various studies have focused on the implementation of LoRaWAN-based WSNs for environmental monitoring applications, such as precision agriculture, air quality assessment, and forest fire detection. The problem of optimal gateway and node placement has been thoroughly investigated utilizing a wide range of techniques, from heuristic methods to complex metaheuristic algorithms. The authors introduced a graph-based strategy for LoRaWAN gateway placement capable of handling arbitrarily large problem instances while guaranteeing full sensor coverage. In both the network planning and gateway deployment phases, collision probabilities are predicted through simulation and used as a key quality metric to guide optimal placement decisions [27].

This work presents two distinct approaches to address the gateway placement problem in LoRaWAN sensor networks. The first approach identifies a minimal set of locations covering all sensor coverage intersections, whereas the second formulates an integer programming optimization model that minimizes the distances between gateways and sensors. The findings demonstrate that automated gateway placement significantly reduces the number of gateways required, compared to conventional or manual deployment strategies [28].

In addition to the LoRaWAN system, which manages LoRaWAN devices, the authors implemented an application-layer retransmission mechanism to improve sensor data completeness. They evaluated the system using several performance indicators, including received signal strength indicator (RSSI), signal-to-noise ratio (SNR), PDR, and data completeness ratio (DCR) [29].

In the agricultural domain, Correia et al. [30] evaluated clustering approaches such as K-Means, Mini-batch K-Means, Bisecting K-Means, and Fuzzy C-Means to optimize gateway placement. Their findings showed that K-Means provided efficient coverage, while Fuzzy C-Means achieved better energy balancing. However, these methods were validated in structured agricultural fields and not in complex forest environments.

This work [9] studied the performance of LoRaWAN for IoT applications in smart agriculture. Using NS-3.45 simulations on a pilot farm, they analyzed different network scenarios and proposed a mathematical model to predict the transmission success rate based on the number of nodes and the transmission interval. The model's results were validated by comparison with the simulations, confirming its accuracy in estimating the reliability of LoRaWAN.

Abreu et al. [31] developed LoRaWISEP+, a planning tool integrating K-Means, K-Medoids, and Fuzzy C-Means to strategically place gateways. They showed that K-Medoids was more robust to outliers, whereas Fuzzy C-Means better optimized the trade-off between energy consumption and coverage. Nevertheless, their work focused on urban and semi-urban deployments rather than forest ecosystems.

For forest monitoring, Etaati et al. [32] introduced a smart forest IoT framework where gateway placement was optimized using meta-heuristics such as Particle Swarm

Optimization (PSO) and Harmony Search. Their results highlighted improved network lifetime and latency. Although highly relevant, this work remained mainly simulation-based, with limited real-world validation.

Study [33] compared K-Means, Fuzzy C-Means (FCM), Gustafson–Kessel clustering, grid-based placement, and random placement using NS-3.45 simulations. Their results showed that the clustering-based methods achieved packet delivery performance comparable to the grid-based approach while requiring fewer gateways in the evaluated scenario.

This work [34] proposed DPLACE, a gateway placement model combining FCM, the Gap statistic, and K-Means to address dynamic IoT scenarios. Their evaluation considered device availability and gateway failures, demonstrating the importance of accounting for network dynamics when planning gateway deployment. These studies are particularly relevant to the present work because they combine clustering-based placement with simulation-based performance evaluation.

Other researchers have considered the influence of environmental and radio-propagation conditions on gateway placement. Cruz et al. [35] developed a placement methodology for a wooded university campus using local radio measurements to calibrate the propagation model and a bio-inspired optimization algorithm to select gateway locations. Modesto et al. [36] subsequently investigated gateway placement using ray-tracing-based channel models and demonstrated that the estimated number of required gateways can vary substantially depending on the propagation model.

Graph-based and optimization-based approaches have also been proposed to address scalability, collision probability, and network capacity. Study [37] investigated placement strategies intended to improve reliability and reduce collision probability in dense LoRaWAN networks. Bhatnagar and Kushwah [38] compared FCM, graph-based placement, Particle Swarm Optimization, and Genetic Algorithms using coverage and energy-related performance indicators. In addition, Savithi and Kaewta [39] formulated gateway selection as a multi-objective problem involving deployment cost and bitrate-related performance. Thepphaeng and Pirak [40] proposed a greedy placement method that accounts for geographic coverage and both uplink and downlink capacity. In the 15-minute reporting scenario, the method places 137 gateways and addresses coverage and communication-capacity requirements in advanced metering infrastructure, while Nugroho et al. [41] presented a four-stage pipeline covering gateway placement, node assignment, radio configuration, and transmission scheduling. Their simulation of 110 nodes reports reductions of up to 85% in average waiting time, 75% in duty cycle, and 80% in per-node energy consumption.

Overall, previous studies have demonstrated the applicability of clustering-based approaches, including K-Means, for WSN and LoRaWAN deployment and gateway placement. However, the considered scenarios, spatial models, optimization objectives, and evaluation methodologies differ across studies. In contrast, this work focuses on a forest fire monitoring scenario in which a geographic representation of a forest area is used to construct the spatial simulation environment. K-Means is applied specifically to determine gateway positions from the spatial distribution of simulated sensor nodes, and the resulting configurations are evaluated using NS-3.45 in terms of PDR, spatial coverage, and energy consumption. This combination provides a reproducible simulation framework for examining K-Means-based gateway placement in a forest-oriented LoRaWAN monitoring scenario.

3. MATERIAL AND METHODS

In this part, the methodological framework created to design, optimize, and assess an IoT-based LoRaWAN network for forest fire monitoring and prevention is covered. The strategy emphasizes optimal deployment, spatial modeling, and simulation-based performance assessment. There are four primary steps in the suggested workflow (Figure 1):

a) The woodland region's geographic modeling
b) Node and gateway deployment and optimization
c) LoRaWAN network simulation in NS-3.45
d) Analyzing and evaluating performance

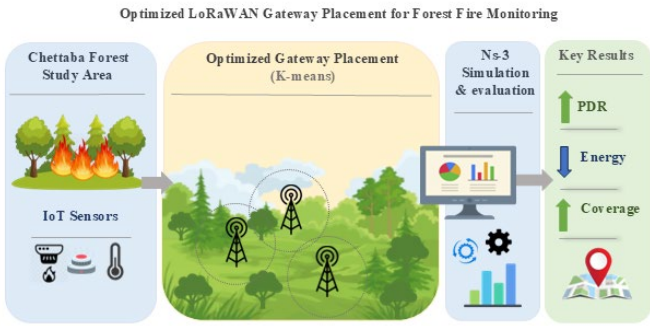


Figure 1. Workflow of the proposed Long Range Wide Area Network (LoRaWAN) gateway optimization approach

3.1 Study area

The case study refers to the Chettaba Forest in Constantine, Algeria (≈36°18′–36°21′ N; 6°26′–6°30′ E). It covers approximately 2,398 ha and is generally between 700 and 1,300 m in altitude, with peaks occasionally exceeding 1,200–1,300 m depending on the local ridges. The dominant vegetation is Mediterranean holm oak (*Quercus ilex*) and Aleppo pine (*Pinus halepensis*) [42].

The Chettaba Forest was chosen as the study site because it is representative of Mediterranean forests that suffer from severe summer drought and intense heat stress. These conditions can contribute to increased fire risk. The long dry season, combined with high surface temperatures and the proximity of the forest to populated areas, can promote rapid fuel desiccation and increase the likelihood of fire ignition. Moreover, recent research on wildfire risk in Algeria highlights that spatial fire susceptibility is best assessed by jointly considering climate-related pressures and satellite-derived environmental indicators [43].

Satellite-based indices were extracted using the Google Earth Engine (GEE) platform, with all calculations spatially restricted to the forest area. Vegetation status was measured using the NDVI, calculated from ground surface reflectance images captured by the Sentinel-2 satellite (Level 2A, standardized). Surface thermal conditions were determined using LST derived from Landsat 8 Collection 2 Level-2 products. Finally, a fire hazard index map was created by combining the vegetation and temperature layers. The NDVI and LST were standardized/reclassified to convergent hazard

levels and then combined to highlight areas exhibiting a decrease in the NDVI (vegetation stress/low humidity) and an increase in LST (thermal stress), which were classified as fire-prone areas. The resulting NDVI, LST, and fire hazard maps were clipped to fit the area of interest to ensure consistency between the geospatial model and the remote sensing-based assessment as shown in Figures 2–4.

The remote sensing analysis is used to characterize the environmental and fire-risk conditions of the selected study area and is not used as a direct input to the gateway placement procedure. The fire-risk map provides environmental context for the modeled forest area, whereas the K-Means gateway placement process uses the geographical coordinates of the simulated sensor nodes as input.

The Chettaba Forest's NDVI map shows that the study area's vegetation vigor varies geographically. The majority of the pixels in the delineated polygon had mild to moderate NDVI values, indicating regions with sparse or stressed vegetation during the summer period. On the other hand, areas of denser and healthier vegetation are reflected in locally occurring patches with comparatively higher NDVI (greener tones). Overall, the observed temperature pattern supports the use of LST as an indicator for characterizing wildfire-risk conditions and is consistent with dry-season Mediterranean conditions. These areas may therefore experience higher fire-risk conditions. The LST map reveals predominantly high surface temperatures across the delineated forest area during summer 2023. Most of the ROI is classified within the highest temperature class (>40 °C), indicating strong thermal stress and favorable conditions for fuel drying. Locally, and mostly in the northwest sector, relatively colder patches (30–40 °C) emerge, indicating topography- and land cover-driven regional heterogeneity. Overall, the observed temperature pattern confirms the value of LST as a critical signal in assessing wildfire risk and is consistent with dry-season Mediterranean conditions.

The fire risk map shows a predominance of high and very high-risk classes within the study area. The strong presence of the red class ("Very High Risk") suggests that, during the analyzed summer period, a large portion of the forest was at risk. The mosaic distribution between the orange and red classes reflects spatial variability linked to vegetation cover heterogeneity (NDVI) and heat stress (LST). These results demonstrate the usefulness of integrating NDVI and LST to characterize spatial variations in environmental fire-risk conditions within the study area.

After defining the Chettaba Forest as the study region, the next step consisted of converting the real forest boundary into a computational geometry suitable for simulation. Geographic coordinates (latitude and longitude) were collected from Google Earth Pro and transformed to the UTM projection system (Zone 31N) to ensure proper metric analysis (Figure 5).

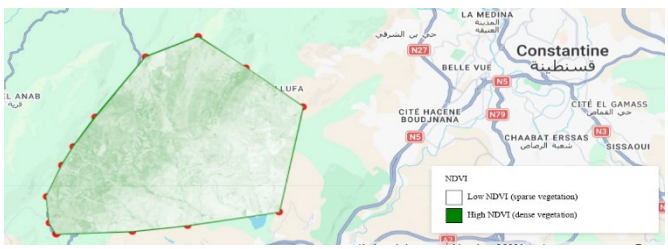


Figure 2. Normalized Difference Vegetation Index (NDVI) map (summer 2023)

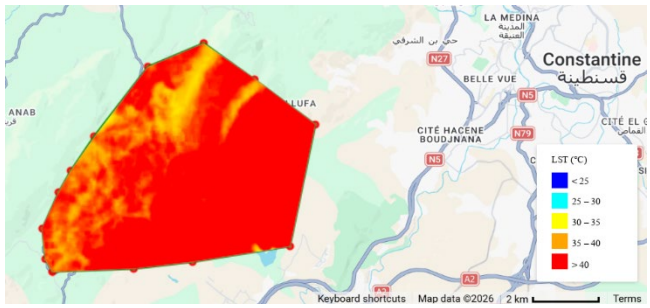


Figure 3. Land surface temperature (LST) map (summer 2023)

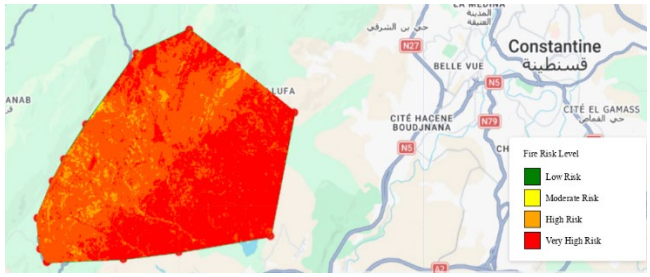


Figure 4. Fire risk map derived from Normalized Difference Vegetation Index (NDVI) and land surface temperature (LST)

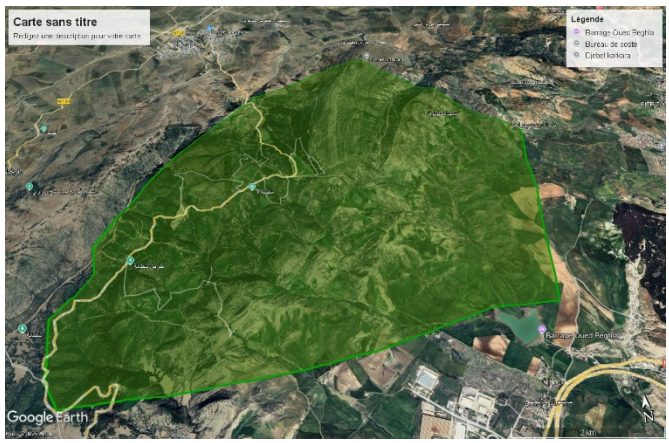


Figure 5. Delineation of the monitored forest area on Google Earth

To adapt the forest region to the circular simulation environment while preserving its surface area, the forest's polygonal shape was processed using the Shoelace (Gauss) technique to calculate its exact surface area. Then, an analogous circular zone with the same area was created to ensure a symmetric simulation environment. The equivalent radius calculated was roughly 3.57 km, which represented the effective size of the forest area employed in the simulated scenarios.

a) Area of a polygon (Gauss's formula: Consider a simple polygon with ordered vertices $(xi, y_i)_i^n = 1$, on note $(x_{n+1}, y_{n+1}) = (x_1, y_1)$. Its range A is

$$A = \frac{1}{2}\left|\sum_{i=1}^{n}(x_i y_{i+1} - y_i x_{i+1})\right| \quad (3)$$

b) Equivalent disk: The radius r of the disk with the same area A as the polygon is defined by

$$r = \sqrt{\frac{A}{\pi}} \tag{4}$$

In our case study, we obtain numerically $r \approx 3.57$ km. The entire chain is reproducible and automated in Python (pandas for tabular I/O, pyproj for geodetic transformations, NumPy for vector operations, Matplotlib for visual control), with systematic checks (presence/order of columns, polygon closure) and the generation of an enriched Comma-Separated Values (CSV) file serving as standardized input for the modeling and simulation stages.

3.2 End device distribution

A predetermined number of end devices (N), ranging from 10 to 2000, were randomly and uniformly distributed within the equivalent circular area. To maintain a realistic density and avoid excessive clustering, a minimum inter-node distance of about 300 m was required between surrounding devices. Each node is a virtual sensor unit that periodically generates environmental data (temperature, humidity, gas, and flame detection). The produced coordinates were saved in a CSV file, which was then imported into the NS-3.45 simulator for node position assignment.

3.3 Gateway placement optimization

To discover the ideal geographic sites for gateways, the K-Means clustering technique was used. The objective of the K-Means-based placement is to minimize the spatial distance between sensor nodes and their assigned gateway. Reducing this distance can contribute to lower transmission losses and improved communication reliability. However, PDR and energy consumption are not directly included in the K-Means objective; their effects are evaluated subsequently through the NS-3.45 simulations (Figure 6).

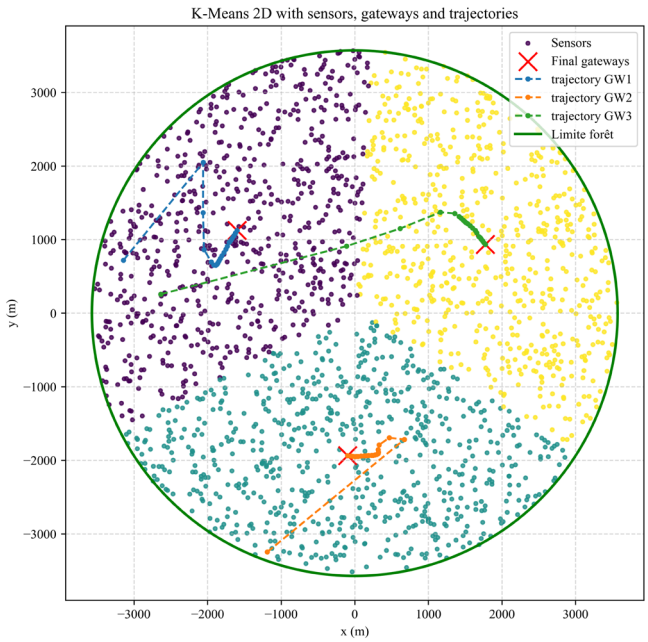


Figure 6. 2D visualization of K-Means clustering ($k = 3$)

The optimization process was built in Python using the following steps:

a) Import the coordinates of all end devices.

b) Use the K-Means clustering technique, with k equal to the number of gateways to be deployed (usually 1, 2, or 3).

c) Save the generated centroids as the ideal gateway coordinates.

d) Create a node-gateway assignment file for the NS-3.45 setup. This technique assures that the gateway deployment is data-driven, replicable, and spatially efficient.

3.4 Gateway deployment scenarios

Four gateway deployment scenarios were examined to determine the impact of gateway placement and density on the performance of the LoRaWAN-based forest fire monitoring system. The monitored forest is represented as a circular region with radius ≈ 3.57 km. The same simulation settings were utilized across all situations (node density, transmission interval, and simulation time). Only the gateway placements and, where applicable, the number of gateways were varied.

3.4.1 Single-gateway central deployment

As a baseline configuration, one gateway was placed at the center of the modeled forest area at (x, y) = (0,0). This scenario shows a modest infrastructure deployment and serves as a baseline for determining the impact of increasing gateway density.

3.4.2 Two-gateway optimized deployment

To increase network dependability, two gateways are installed with the suggested K-Means-based optimization technique. The sensor node locations were partitioned into K = 2 clusters, and gateway coordinates are assigned to the cluster centroids.

3.4.3 Three-gateway optimized deployment

To investigate scalability and the impact of gateway density, the optimized technique was also tested with three gateways. In this scenario, K-Means was applied with K = 3, and the generated centroids were used to identify gateway sites. This scenario is meant to give design insights into the advantages of expanding the number of gateways with optimum placement.

3.4.4 Two-gateway random deployment

For the random baseline, two gateways were placed at randomly selected locations within the modeled forest area. This configuration was evaluated using the same network settings as the two-gateway K-Means-based deployment to ensure a consistent comparison.

3.5 Performance evaluation metrics

The performance of the simulated deployments was evaluated using three main metrics:

3.5.1 Packet Delivery Ratio

PDR is a key performance indicator used to evaluate the reliability and efficiency of data transmission in LoRaWAN-based sensor networks. It is defined as the ratio between the total number of packets successfully received by the gateway(s) and the total number of packets transmitted by the end devices during the simulation period. This metric provides an estimate of the reliability of the communication system in delivering sensing data from the forest environment to the

gateway.

$$\mathrm{PDR} = \frac{N_{\mathrm{received}}}{N_{\mathrm{sent}}} \quad (5)$$

A high PDR value indicates that most packets are successfully delivered, reflecting good network connectivity and minimal interference or collisions [44], whereas a low PDR reveals transmission losses due to factors such as long distances, channel congestion, collisions in the shared spectrum, or poor SNR. In this work, the PDR was obtained directly from the "LoraPacketTracker" integrated into the NS-3.45 LoRaWAN module, which monitors each packet's transmission and reception events across the entire network.

3.5.2 Area coverage

Area coverage is one of the most important metrics for evaluating the effectiveness of a WSN, as it quantifies the fraction of the monitored region that is effectively sensed by the deployed sensor nodes, calculated geometrically using node coordinates and sensing radius. In this work, the area coverage C_A is estimated using the Monte Carlo method, which provides an unbiased and flexible estimation for arbitrary geometries (disk, polygon) and heterogeneous sensing radii. A large number N of random points p_j were uniformly generated inside the considered region $\mathcal{R}$. Each point is marked as covered if there exists at least one sensor node x_i such that the Euclidean distance between them satisfies $d(p_j, x_i) \leq \mathcal{R}_{s,i}$, where $\mathcal{R}_{s,i}$ is the sensing radius of node i. The estimated coverage ratio is therefore given by:

$$\hat{C}_A = \frac{1}{N}\sum_{j=1}^{N} 1\left\{\min_i d(p_j, x_i) \leq \mathcal{R}_{s,i}\right\} \quad (6)$$

In our simulation, the coverage was calculated over a circular region representing the forest area, with sensing radii ranging from 100 m [45-47].

3.5.3 Energy consumption

Energy consumption of each end device was evaluated using the LoraRadioEnergyModel integrated within the NS-3.45 LoRaWAN module. This model accounts for the power drawn by the transceiver in different operational states, including transmission, reception, idle, and sleep modes [48]. The total energy consumed by a device during the simulation period was expressed as:

$$E_{\mathrm{consumed}} = E_{\mathrm{initial}} - E_{\mathrm{remaining}} \quad (7)$$

where, E_{initial} is the initial battery energy and $E_{\mathrm{remaining}}$ is the residual energy at the end of the simulation. The per-node consumption is then averaged to assess the overall network energy efficiency.

3.6 Network simulation setup (NS-3.45)

In this study, LoRaWAN network communication was simulated using NS-3.45 with the LoRaWAN module developed by Magrin et al. [49]. To align with the objectives of our work, the module has been slightly adapted in order to design simulation scenarios that mimic real-world deployments of LoRaWAN for forest fire prevention and detection. The experiments were designed to evaluate network performance under different conditions, with emphasis on PDR, area coverage, and energy consumption as the main performance metrics (Figure 7). Before presenting the numerical results, we describe in detail the main assumptions underlying the simulation setup.

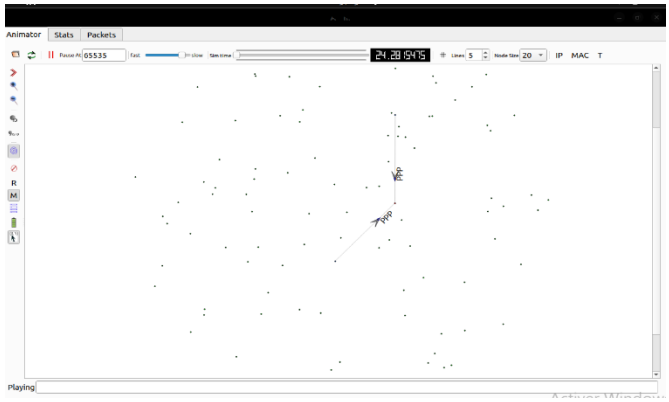


Figure 7. NetAnim visualization of the simulated Long Range Wide Area Network (LoRaWAN) network

The forest is represented as an open circular area with a radius ≈ 3.57 km.

To investigate the impact of gateway density and placement, we consider three different configurations: (i) a single gateway, (ii) two gateways, and (iii) three gateways, and (iv) two randomly placed gateways. In the baseline configuration, one gateway was placed at the center of the circular region. For the configurations with two and three gateways, the gateway locations were determined using the K-Means clustering algorithm applied to the spatial distribution of the sensor nodes. The cluster centroids returned by K-Means were used as candidate gateway positions, which provide an approximately optimized deployment that reduces the average distance between nodes and their serving gateway.

All nodes were configured to use LoRaWAN Class A communication, which is the most energy-efficient mode for battery-powered devices. Each node periodically transmitted uplink packets to the gateway containing environmental data relevant to fire detection. Packets were transmitted in unconfirmed mode. If no acknowledgment is received from the gateway during the first and second reception windows, the packet is considered lost. These packets are not retransmitted, which allows us to model realistic IoT deployments where energy efficiency is prioritized over repeated transmissions.

The payload size of each message was set to 23 bytes, representing typical sensing data. The data generation was periodic, with a fixed transmission interval per experiment. For every configuration defined by the number of nodes, multiple simulations were carried out by varying the interval between successive transmissions. This inter-packet interval is of particular importance since it determines the network load and influences both channel collisions and overall reliability. The transmission intervals considered in the simulations ranged from 60 to 300 s. These values were selected to represent different network-load conditions. These limits reflect two possible operational strategies: frequent transmissions in critical conditions (e.g., high fire risk), or sparse transmissions in normal conditions to preserve energy.

At the beginning of each simulation, the SF of every node was determined based on the received signal strength at the

gateway. The allocation covers values between SF7 and SF12, in accordance with LoRaWAN specifications. Each simulation lasted 24 hours, long enough to capture both short-term and periodic behaviors of the network. PDR was used as the primary communication performance metric in this study. This metric provides an estimate of the reliability of packet delivery from the simulated end devices to the gateways.

In addition to PDR, energy consumption was also evaluated. For each end device, the energy consumed by the radio module in the main operating states, including transmission, reception, idle, and sleep, was monitored throughout the simulation. The total energy consumption is then aggregated over all nodes. From this information, we derive both the average energy consumed per node and the energy cost per successfully delivered packet. These indicators are particularly important for forest fire detection systems, where sensor nodes are battery-powered and are expected to operate autonomously over long periods without maintenance.

Furthermore, we consider an area coverage metric to characterize how well the monitored forest region is effectively observed by the sensor network. Each node was assumed to cover a sensing disc corresponding to its detection radius. The area coverage was defined as the proportion of the total forest area that is located within the sensing range of at least one node. This metric reflects the spatial quality of monitoring: a higher coverage value indicates that a larger fraction of the forest is under surveillance and that potential fire ignition points are more likely to be detected.

In this work, the PDR was selected as the primary performance metric. This choice is motivated by the fact that, in forest fire detection systems, the reliability of data transmission is more critical than throughput. While throughput measures the overall data rate of the network, it does not necessarily reflect whether vital sensing information reaches the gateway in emergency situations.

On the other hand, energy consumption and spatial coverage were also crucial, because nodes must operate under strict power constraints while ensuring that the majority of the forest area is effectively monitored. The combination of PDR, energy, and area coverage therefore provides a more complete evaluation of the network's ability to deliver critical sensing information under realistic constraints.

For evaluation purposes, five different transmission intervals are considered in our experiments: 60, 120, 180, 240, 300 seconds. These intervals represent different offered network loads, ranging from more frequent transmissions to less frequent transmissions. These transmission intervals were evaluated for different network sizes, with 10, 50, 100, 300, 600, 1000, and 2000 end devices. By analyzing these configurations, we were able to capture the trade-offs between energy efficiency, spatial monitoring quality, and communication reliability in forest fire detection networks.

The NS-3.45 simulation followed the methodology shown below: Node Creation: Create all end devices and gateways based on the input coordinates. Mobility Configuration: To emulate ground-mounted sensors, use static placements with a set elevation (z = 1.2 m). LoRaWAN Configuration: Assign an application layer to each node to allow for periodic data transfer. Data logging includes keeping track of all transmission and reception events, as well as energy usage and signal parameters. Result Export: Save simulation results as trace files and CSV files for analysis using Python and Gnuplot. This method allows for precise control and repeatability for each network setup. The main simulation parameters are summarized in Table 1.

Table 1. The main simulation parameters used in this study

Parameters	Value
Simulation time (seconds)	86,400 / 24 h
Forest-area radius (m)	3571.83
Number of nodes	10–2,000
Number of gateways (G)	1–3
Packet size (bytes)	23
Duration of the transmission interval (seconds)	60–300 / 1 m–5 m
Antenna height (m)	15
Nodes height (m)	1.2
Positions of nodes	Distributed uniformly
Mobility of nodes and gateway	Constant Position
Bandwidth (kHz)	125
Frequency (MHz)	868
Node mobility model	Constant Position
Gateway mobility mode	Constant Position
Propagation loss model	Log-Distance
Path-loss exponent	3.76
Reference distance	7.7 m
Propagation delay model	Constant Speed
Channel model	LoraChannel
End-device transmission power	14 dBm (default/initial)
Spreading factor	Automatically assigned (SF7–SF12)
Receiver sensitivity – gateway	SF7: −130; SF8: −132.5; SF9: −135; SF10: −137.5; SF11: −140; SF12: −142.5 dBm
Receiver sensitivity – end device	SF7: −124; SF8: −127; SF9: −130; SF10: −133; SF11: −135; SF12: −137 dBm
Interference model	LoraInterferenceHelper
Collision matrix	Goursaud
Antenna configuration	Default configuration
End-device initial energy	25,920 J
End-device supply voltage	3.0 V
Transmission current	28 mA
Reception current	11 mA
Idle current	1.4 mA
Sleep current	1 µA

4. RESULTS

This section presents the results of NS-3.45 simulations conducted to assess the effectiveness of the proposed LoRaWAN gateway placement strategy for forest fire monitoring. The performance evaluation focuses on crucial performance indicators such as PDR, area coverage, and energy consumption. These metrics were evaluated in various network configurations by adjusting the number of end devices, the number of gateways, and the transmission interval (ranging from 60 to 300 s). The simulation results for the different deployment scenarios are summarized in Tables 2–14. The results were organized to first examine the impact of gateway density under optimized deployment, followed by a fair comparison between optimized and random gateway placement using the same number of gateways.

Table 2. Results of the Packet Delivery Ratio (PDR) for all simulations with a single gateway

Number of Nodes	Duration of the Transmission Interval (Seconds)				
	60	120	180	240	300
10	1	1	1	1	1
50	0.993	1	1	1	1
100	0.98	0.99	1	1	1
300	0.92	0.954	0.973	0.979	0.984
600	0.831	0.91	0.936	0.952	0.961
1000	0.739	0.856	0.899	0.924	0.939
2000	0.537	0.723	0.805	0.851	0.877

Table 3. Results of the PDR for all simulations with two gateways

Number of Nodes	Duration of the Transmission Interval (Seconds)				
	60	120	180	240	300
10	1	1	1	1	1
50	0.993	1	1	1	1
100	0.987	0.997	0.997	1	1
300	0.946	0.976	0.984	0.987	0.99
600	0.885	0.938	0.951	0.964	0.973
1000	0.837	0.915	0.943	0.955	0.961
2000	0.676	0.821	0.877	0.905	0.923

Table 4. Results of the PDR for all simulations with three gateways

Number of Nodes	Duration of the Transmission Interval (Seconds)				
	60	120	180	240	300
10	1	1	1	1	1
50	1	1	1	1	1
100	0.984	0.994	0.997	0.997	0.997
300	0.967	0.987	0.991	0.996	0.998
600	0.925	0.960	0.972	0.978	0.983
1000	0.884	0.940	0.958	0.969	0.976
2000	0.754	0.879	0.918	0.939	0.952

Table 5. Results of the PDR for all simulations with two gateways under random gateway placement

Number of Nodes	Duration of the Transmission Interval (Seconds)				
	60	120	180	240	300
10	1	1	1	1	1
50	0.987	0.994	0.994	0.994	0.994
100	0.989	0.994	0.994	0.997	1
300	0.946	0.978	0.983	0.987	0.993
600	0.863	0.917	0.937	0.951	0.961
1000	0.752	0.869	0.917	0.937	0.947
2000	0.512	0.738	0.820	0.863	0.887

Table 6. Total energy consumption versus transmission interval for different network densities with one gateway

Number of Nodes	Duration of the Transmission Interval (Seconds)				
	60	120	180	240	300
10	113.560911	58.130456	39.653639	30.415229	24.872182
50	605.36451	309.43226	210.788175	161.466129	131.872906
100	1356.014517	691.507259	470.004846	359.25364	292.802909
300	4055.338894	2068.705942	1405.76872	1074.853887	875.651656
600	8125.874548	4139.088652	2811.124806	2150.552176	1751.644893
1000	13513.262739	6881.65411	4672.114064	3570.841773	2913.931236
2000	27335.91239	13875.85012	9414.663969	7195.010467	5861.528677

Table 7. Total energy consumption versus transmission interval for different network densities with two gateways

Number of Nodes	Duration of the Transmission Interval (Seconds)				
	60	120	180	240	300
10	106.04892	54.374457	37.14964	28.53723	23.369783
50	551.541986	282.520992	192.847326	148.010496	121.1084
100	1150.560205	588.738377	401.131508	307.598628	251.478905
300	3512.55333	1795.220813	1223.013632	937.510238	766.671457
600	6975.157022	3562.360444	2428.166476	1860.294227	1521.073067
1000	11847.336625	6043.900506	4115.986687	3152.285452	2577.192534
2000	23587.481892	12000.84446	8170.497764	6262.304465	5112.521386

Table 8. Total energy consumption versus transmission interval for different network densities with three gateways

Number of Nodes	Duration of the Transmission Interval (Seconds)				
	60	120	180	240	300
10	106.04892	54.374457	37.14964	28.53723	23.369783
50	537.756588	275.628293	188.252194	144.564147	118.35132
100	1061.654881	544.285715	371.496402	285.667606	233.69784
300	3205.46353	1640.488918	1119.49719	860.159012	704.561592
600	6404.642997	3275.07367	2236.075697	1716.287546	1405.867725
1000	10712.784328	5475.733757	3736.47595	2867.25984	2349.739366
2000	21509.637158	10958.08723	7472.018244	5738.211087	4693.389342

Table 9. Total energy consumption for different numbers of nodes and transmission intervals with two gateways under random placement

Number of Nodes	Duration of the Transmission Interval (Seconds)				
	60	120	180	240	300

10	127.346312	65.023151	44.24877	33.861577	27.62926
50	764.515888	389.007938	263.838626	201.25397	163.703179
100	1539.101362	783.591821	531.033802	405.320659	329.420281
300	3982.762668	2030.822555	1380.486719	1055.615055	861.896673
600	16214.697688	9329.160549	6297.780219	4761.746411	3838.918779
1000	27419.448426	15643.110097	10555.480012	7967.798508	6424.585676
2000	55615.167711	31501.284958	21162.876872	16007.114498	12886.383037

Table 10. Average energy consumption per node versus transmission interval for different network sizes with one gateway

Number of Nodes	Transmission Interval (Seconds)				
	60	120	180	240	300
10	11.3560911	5.8130456	3.9653639	3.0415229	2.4872182
50	12.1072902	6.1886452	4.2157635	3.22932258	2.63745812
100	13.56014517	6.91507259	4.70004846	3.5925364	2.92802909
300	13.5177963133	6.8956864733	4.6858957333	3.58284629	2.9188388533
600	13.5431242466	6.8984810866	4.68520801	3.5842536266	2.919408155
1000	13.513262739	6.88165411	4.672114064	3.570841773	2.913931236
2000	13.667956195	6.93792506	4.7073319845	3.5975052335	2.9307643385

Table 11. Average energy consumption per node versus transmission interval for different network sizes with two gateways

Number of Nodes	Transmission Interval (Seconds)				
	60	120	180	240	300
10	10.604892	5.4374457	3.714964	2.853723	2.3369783
50	11.03083972	5.65041984	3.85694652	2.96020992	2.422168
100	11.50560205	5.88738377	4.01131508	3.07598628	2.51478905
300	11.7085111	5.9840693766	4.0767121066	3.1250341266	2.5555715233
600	11.6252617033	5.9372674066	4.0469441266	3.1004903783	2.5351217783
1000	11.847336625	6.043900506	4.115986687	3.152285452	2.577192534
2000	11.793740946	6.00042223	4.085248882	3.1311522325	2.556260693

Table 12. Average energy consumption per node versus transmission interval for different network sizes with three gateways

Number of Nodes	Transmission Interval (Seconds)				
	60	120	180	240	300
10	10.604892	5.4374457	3.714964	2.853723	2.3369783
50	10.75513176	5.51256586	3.76504388	2.89128294	2.3670264
100	10.61654881	5.44285715	3.71496402	2.85667606	2.3369784
300	10.6848784333	5.4682963933	3.7316573	2.8671967066	2.34853864
600	10.674404995	5.4584561166	3.7267928283	2.8604792433	2.343112875
1000	10.712784328	5.475733757	3.73647595	2.86725984	2.349739366
2000	10.754818579	5.479043615	3.736009122	2.8691055435	2.346694671

Table 13. Average energy consumption per node for different numbers of nodes and transmission intervals with two gateways under random placement

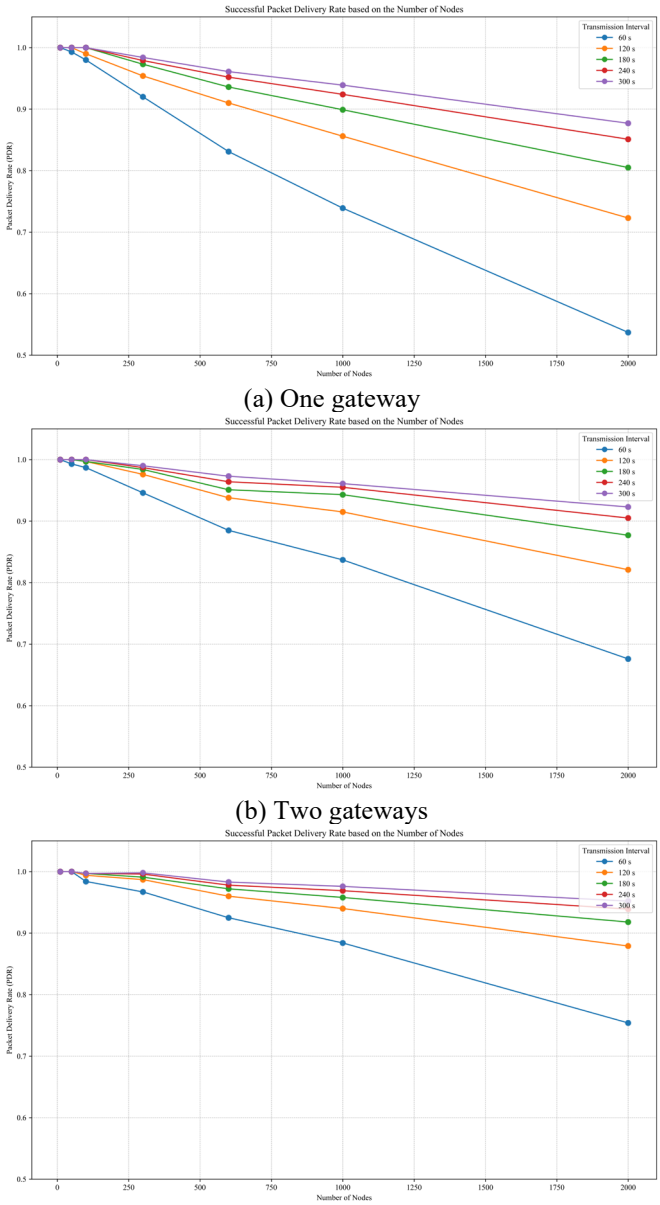
Number of Nodes	Transmission Interval (Seconds)				
	60	120	180	240	300
10	12.734631	6.502315	4.424877	3.386158	2.762926
50	15.290317	7.780158	5.276772	4.025079	3.274063
100	15.391014	7.835918	5.310338	4.053207	3.294203
300	13.275876	6.769408	4.601622	3.518717	2.872989
600	27.024496	15.548601	10.496300	7.936244	6.398198
1000	27.419448	15.643110	10.555480	7.967799	6.424586
2000	27.807584	15.750642	10.581438	8.003557	6.443192

Table 14. Results of the area coverage % for all simulations

Number of Nodes	Coverage
10	0.75%
50	3.752%
100	7.368%
300	20.97%
600	37.038%
1000	53.508%
2000	77.836%

4.1 Impact of gateway density (optimized deployment)

This subsection analyzes the impact of gateway density on network performance in the case of optimized deployment. Three configurations were considered: a single gateway placed at the center of the forest area (1 GW), two gateways deployed according to the optimized strategy (2 GW), and three gateways deployed in an optimized manner (3 GW). Performance was evaluated for different numbers of end devices and transmission intervals.

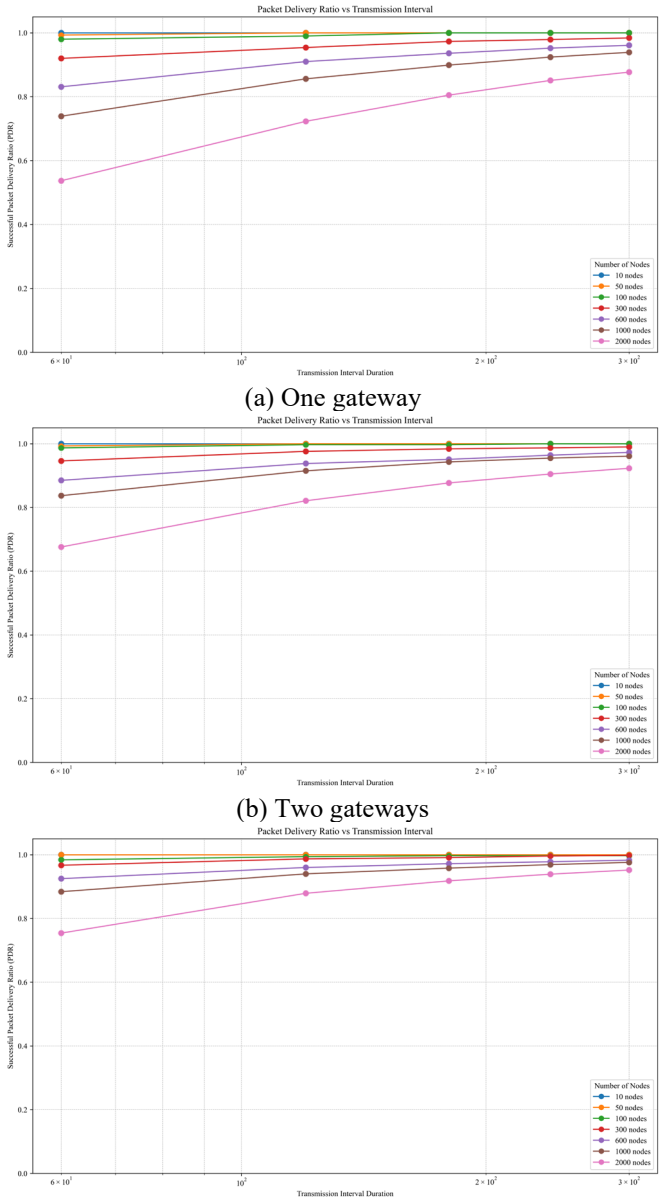


(a) One gateway

(b) Two gateways

(c) Three gateways

Figure 8. Packet Delivery Ratio (PDR) vs. the number of sensor nodes for different transmission intervals and gateway configurations



(a) One gateway

(b) Two gateways

(c) Three gateways

Figure 9. Packet Delivery Ratio (PDR) vs. transmission interval for different numbers of sensor nodes and gateway configurations

4.1.1 Packet Delivery Ratio vs. number of nodes

Figure 8 shows the evolution of the PDR as a function of the number of nodes for different transmission interval durations. In the case of a single gateway (Figure 8(a)), the PDR decreases rapidly as network density increases, particularly for short transmission intervals. This degradation becomes significant for high-density scenarios, indicating the limitations of minimal deployment in terms of communication reliability. With two optimally deployed gateways (Figure 8(b)), a noticeable improvement in PDR is observed for all configurations. The network maintains higher levels of reliability, even when the number of nodes reaches 1,000 and 2,000, demonstrating the benefit of increased gateway density with optimized placement. The configuration with three optimized gateways (Figure 8(c)) offers the best overall performance. The PDR remains high and relatively stable across the entire range of densities studied, including for short transmission intervals. This configuration demonstrates a better ability to support high network loads.

4.1.2 Packet Delivery Ratio vs. transmission interval

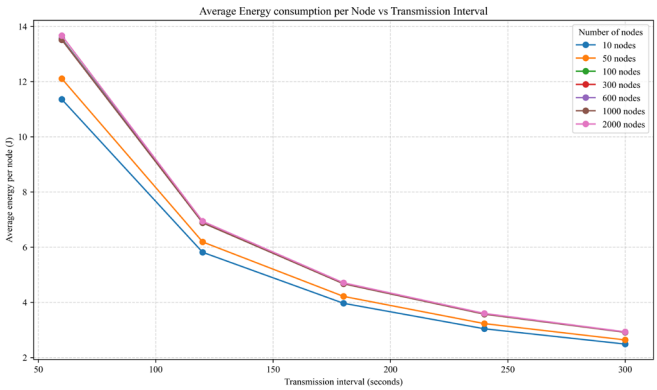
Figure 9 illustrates the variation in PDR as a function of transmission interval duration for different numbers of nodes. For all three configurations, increasing the transmission interval resulted in higher PDR values. However, this effect was more pronounced in the case of a single gateway, while configurations with two and three gateways show greater robustness under high loads, even for shorter transmission intervals. For example, at N = 2000, increasing the transmission interval from 60 to 300 s resulted in higher PDR values across the evaluated gateway configurations.

4.1.3 Energy consumption

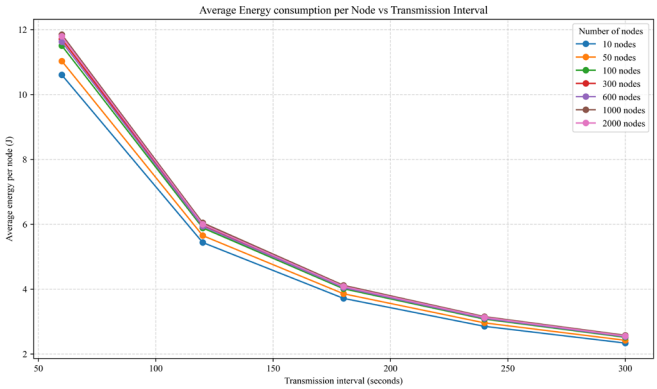
This subsection analyzes the impact of gateway density on network energy consumption in the case of optimized deployment. Three configurations were considered: a single gateway (1 GW), two optimized gateways (2 GW), and three optimized gateways (3 GW). The analysis focuses on average energy consumption per node and total energy consumed,

based on transmission interval duration and network density. Figure 10 shows the evolution of average energy consumption per node as a function of transmission interval duration for different numbers of nodes. In all three configurations, a significant decrease in average energy consumption is observed as the transmission interval increases. This trend is particularly pronounced in the case of a single gateway (Figure 10(a)), where the communication load per node is higher.

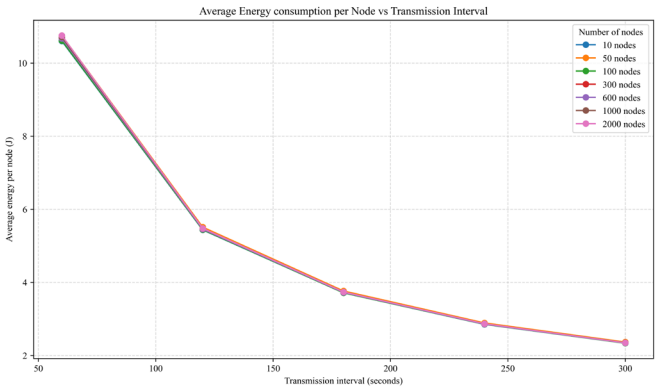
With two optimally deployed gateways (Figure 10(b)), average energy consumption per node is reduced for all network densities. The configuration with three optimized gateways (Figure 10(c)) has the lowest and most stable average energy consumption values, particularly in high-density scenarios, indicating better distribution of the communication load between gateways.



(a) One gateway



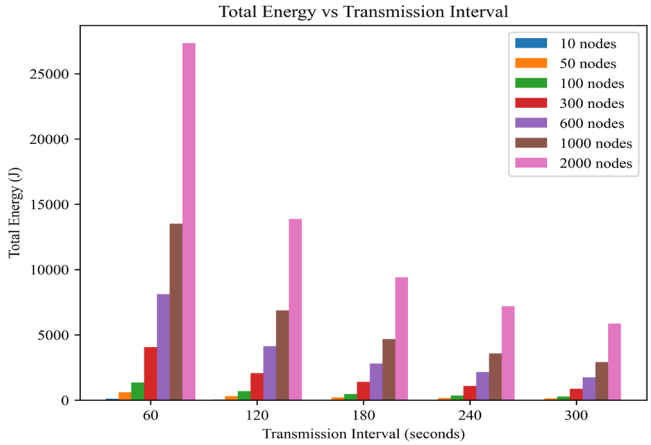
(b) Two gateways



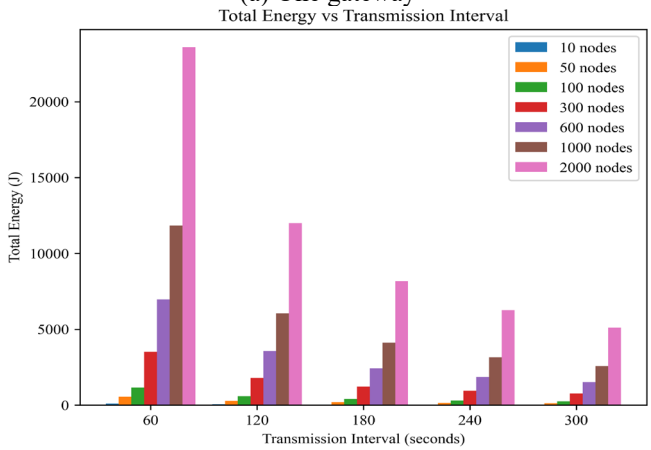
(c) Three gateways

Figure 10. Average energy consumption per node vs. transmission interval

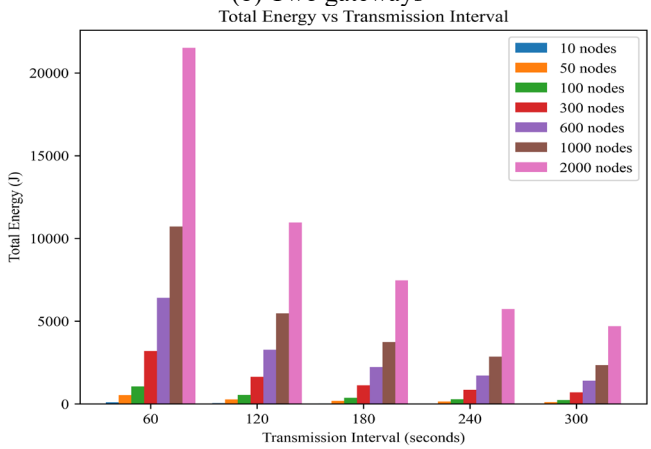
Figure 11 shows the total energy consumption as a function of the transmission interval duration. The results show that total energy increases with the number of sensor nodes, while it decreases as the transmission interval becomes longer. Consistent with previous results, increasing the number of gateways in an optimized deployment reduces total energy consumption, particularly in high-density network scenarios. This is because a longer transmission interval reduces the number of packets sent by each node, which decreases the radio module's activity time, the number of node wake-ups, and therefore overall energy consumption.



(a) One gateway



(b) Two gateways



(c) Three gateways

Figure 11. Total energy consumption vs. transmission interval

Thus, less frequent transmissions extend the life of the nodes, which is essential for low-power IoT applications such as forest fire detection. Regardless of the transmission interval, the total energy increases with the number of nodes deployed in the network. This increase is due to increased radio channel

contention and increased collisions.

Overall, these results highlight that increasing the density of gateways, when combined with optimized placement, helps improve the energy efficiency of the network and limit energy consumption, which is an essential criterion for forest fire monitoring systems deployed over large areas.

4.2 Area coverage vs. number of nodes

While PDR captures communication success, it does not indicate how much of the forest is sensed at any time. To quantify the spatial effectiveness of the deployment, we next evaluate Area Coverage using Monte Carlo estimation. Area coverage measures the fraction of the forest region that falls within at least one node's sensing radius RS. Using the same node layouts as in the PDR experiments, we estimate coverage by Monte Carlo inside the equivalent forest disk. Figure 12 shows that Area coverage grows non-linearly with the number of sensor nodes: it rises from 0.75% (10 nodes) to 3.75% (50 nodes) and 7.37% (100 nodes). It then accelerates to 20.97% (300 nodes), 37.04% (600 nodes), 53.51% (1000 nodes), and 77.84% (2000 nodes).

The initial rapid gains occur because new nodes add largely uncovered regions; at higher densities, coverage saturates as sensing disks overlap, so each additional node contributes less new area (diminishing returns). To approach ≥90% coverage with the current random deployment, one would likely need more than 2000 nodes; alternatively, increasing the sensing radius Rs and/or targeted placement of extra nodes in uncovered gaps can reach the same target more efficiently.

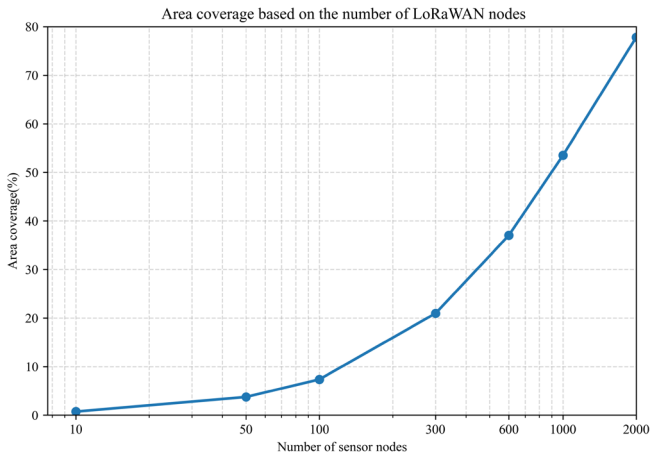


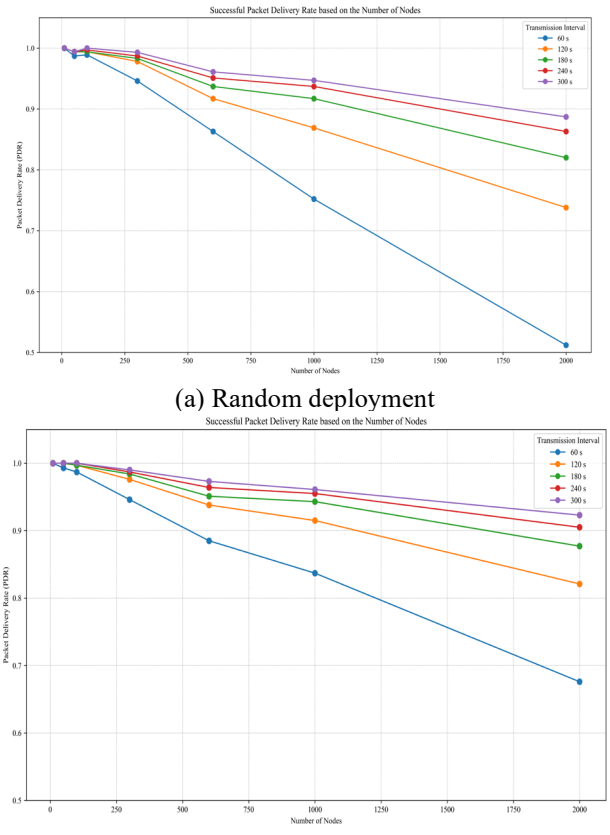
Figure 12. Area coverage as a function of the number of Long Range Wide Area Network (LoRaWAN) sensor nodes

4.3 Comparison between optimized and random deployment (two gateways)

This subsection compares the performance of the optimized gateway deployment with a random baseline using the same number of gateways (two gateways). The objective is to isolate the impact of gateway placement strategy while keeping all other simulation parameters unchanged, including network density and transmission interval.

Figure 13 compares the PDR based on the number of sensor nodes for different transmission interval durations in the case of two gateways. Figure 13(a) corresponds to the random deployment of gateways, while Figure 13(b) illustrates the optimized deployment based on the K-Means algorithm. The results show that, for low network densities, both deployment strategies achieve PDR values close to unity. However, as the number of sensor nodes increases, random deployment suffers a more marked degradation in PDR, particularly for short transmission intervals. Conversely, optimized deployment maintains a higher level of reliability across all network sizes considered.

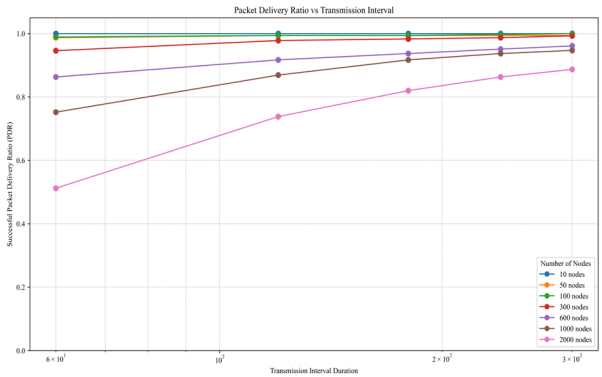
Figure 14 shows the evolution of the PDR as a function of the transmission interval duration for different numbers of sensor nodes. Similarly, Figure 14(a) corresponds to random deployment, while Figure 14(b) represents optimized deployment. The results indicate that an increase in the transmission interval improves the PDR for both strategies. However, optimized gateway placement consistently offers better performance, particularly in high-density scenarios (1,000 and 2,000 nodes), where the difference between the two approaches becomes significant.



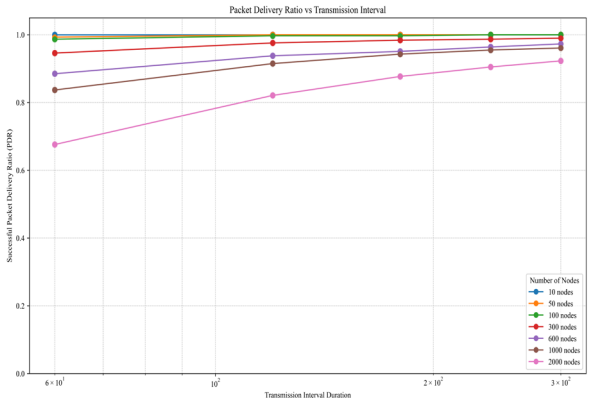
(a) Random deployment

(b) Optimized deployment

Figure 13. Packet Delivery Ratio (PDR) as a function of the number of sensor nodes

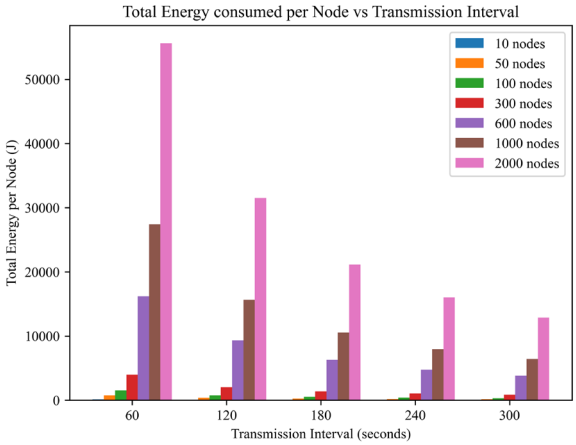


(a) Random deployment

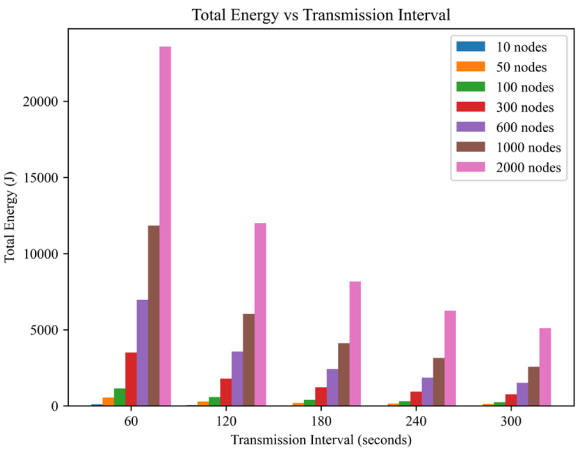


(b) Optimized deployment

Figure 14. Packet Delivery Ratio (PDR) as a function of transmission interval duration



(a) Random deployment



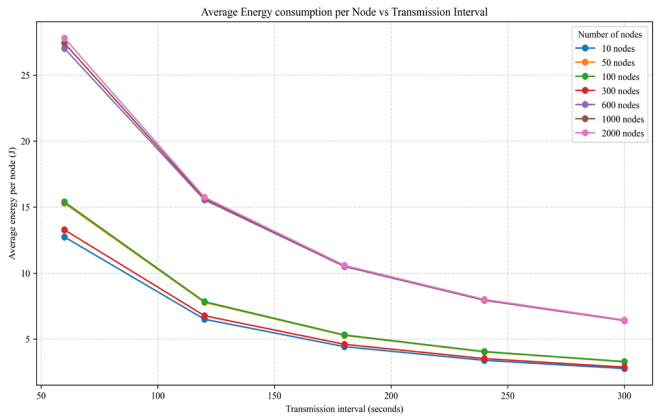
(b) Optimized deployment

Figure 15. Total energy consumption

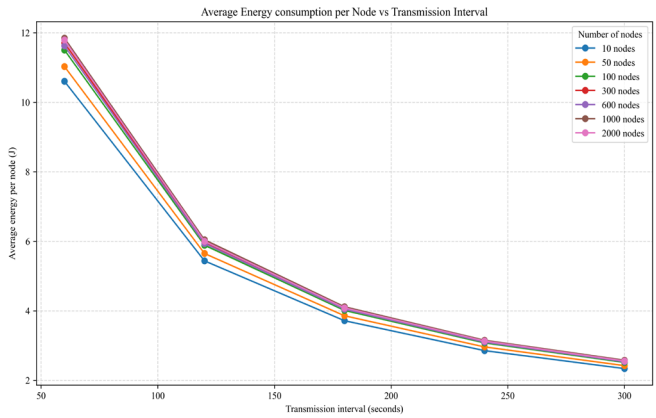
Figure 15 shows the evolution of total energy consumption as a function of transmission interval duration for different numbers of sensor nodes, in the case of two gateways. Figure 15(a) corresponds to random deployment of gateways, while Figure 15(b) illustrates optimized deployment. The results show that, for both deployment strategies, the energy consumed per node decreases as the transmission interval length increases. This trend is observed for all network densities, which can be explained by the reduction in the number of transmissions performed over a given period. Furthermore, for the same network configuration, optimized deployment systematically leads to lower energy consumption than random deployment, particularly in high-density scenarios (600 to 2,000 nodes). This difference becomes more pronounced for short transmission intervals, where the network load is higher.

Figure 16 shows the evolution of average energy consumption per node as a function of transmission interval duration for different network densities, in the case of two gateways. Figure 16(a) corresponds to random gateway deployment, while Figure 16(b) illustrates optimized deployment. The results show that, for both deployment strategies, the average energy consumption per node decreases as the transmission interval length increases. This trend is observed for all network densities and reflects the reduction in the number of transmissions made by the sensor nodes. When comparing the two approaches, optimized deployment consistently reduces average energy consumption per node compared to random deployment. This reduction is particularly noticeable in high-density network scenarios (1,000 and 2,000 nodes), where optimized gateway placement helps improve the overall energy efficiency of the system.

These results confirm that optimized gateway placement simultaneously improves communication reliability and energy efficiency, two key requirements for large-scale forest fire monitoring systems.



(a) Random deployment



(b) Optimized deployment

Figure 16. Average energy consumption per node

5. DISCUSSION

This section discusses the main results obtained from the NS-3.45 simulations, highlighting the impact of gateway placement and density on communication reliability, energy

efficiency, and spatial coverage of the forest fire monitoring system.

The results relating to the PDR highlight the decisive role played by gateway density when an optimized deployment is adopted. In the case of a single gateway, even when centrally located, communication reliability declines rapidly as the number of sensor nodes increases, particularly for short transmission intervals. This degradation reflects the limitations of a minimal infrastructure when faced with high traffic loads, which are typical of large-scale forest monitoring systems.

The addition of a second gateway deployed according to the optimized strategy significantly improves the PDR across all configurations studied. This improvement is due to better spatial distribution of sensor nodes between gateways, which reduces channel congestion and limits collisions. As a result, the network becomes more robust in the face of increased node density and traffic volume. The three-gateway optimized configuration offers the best performance in terms of PDR, particularly in high network density scenarios and for short transmission intervals. Maintaining high PDR values under these conditions indicates an increased ability of the network to support heavy loads while ensuring reliable communication. This demonstrates that increasing gateway density, when combined with optimized placement, is an effective lever for improving network scalability.

In the context of forest fire monitoring, these results are particularly important. Early fire detection relies on the rapid and reliable transmission of environmental data, often in situations of network congestion. A high PDR ensures that critical information about fire-prone conditions or early signs of fire reaches the monitoring server without significant loss. Thus, increasing the number of gateways, combined with an optimized placement strategy, directly contributes to enhancing the operational reliability of forest fire monitoring systems.

These observations confirm that gateway density should not be considered independently of their positioning. Optimized deployment allows full advantage to be taken of the increase in the number of gateways, maximizing gains in terms of communications reliability and ensuring performance adapted to the requirements of critical environmental applications.

In addition to the PDR analysis, the energy consumption study makes it possible to assess the long-term sustainability of the network. The results obtained for optimized deployment clearly highlight the influence of the number of gateways on the energy efficiency of the LoRaWAN network. In single-gateway scenarios, the average and total energy consumption is relatively high, particularly for short transmission intervals and high network densities. This situation can be explained by the concentration of traffic towards a single gateway.

The introduction of a second gateway deployed in an optimized manner significantly reduces energy consumption. By distributing the sensor nodes across multiple gateways, the communication load is better balanced, which limits collisions and reduces the number of unsuccessful transmissions. This improvement is particularly noticeable in high-density scenarios, where energy consumption per node decreases significantly compared to a single gateway configuration.

The three-gateway optimized configuration offers the best overall energy performance. The results show lower and more stable average energy consumption per node, regardless of the number of sensor nodes. This stability indicates a better ability of the network to absorb high loads while maintaining satisfactory energy efficiency. Increasing the number of gateways reduces communication distances and improves radio link quality and, consequently, lowers energy consumption.

In addition, increasing the transmission interval duration also helps reduce energy consumption, regardless of the number of gateways. However, this effect is more pronounced in low-density gateway configurations, while optimized deployments with two and three gateways offer better energy robustness even for shorter transmission intervals. This suggests that optimizing gateway placement can partially offset the constraints associated with more frequent traffic. In the context of large-scale forest fire monitoring, these results are particularly relevant. Since sensor nodes are typically battery-powered and deployed in remote areas, reducing energy consumption is a key factor in extending network lifetime and ensuring continuous monitoring. Thus, increasing gateway density, when combined with optimized placement, is an effective solution for improving the energy efficiency of LoRaWAN networks dedicated to environmental monitoring applications.

While reducing energy consumption is essential to extending the network's lifespan, it must be combined with sufficient spatial coverage to ensure effective monitoring of the forest area. Analysis of spatial coverage highlights the effectiveness of deploying sensor nodes for monitoring forest fires. The results show that coverage of the forest area increases non-linearly with the number of nodes. At low densities, adding sensors allows for rapid expansion of the monitored area, which improves early fire detection capabilities.

As node density increases, coverage progression slows down due to overlapping detection areas, reflecting a phenomenon of diminishing returns. In this case, increasing the number of randomly deployed sensors becomes less effective in improving overall coverage. These results suggest that, for large-scale forest fire monitoring applications, achieving high levels of coverage requires either a large number of nodes or the adoption of more effective strategies, such as increasing the detection radius or targeted placement of sensors in uncovered or high-risk areas. A balanced deployment design is therefore essential to ensure effective spatial monitoring while limiting costs and energy consumption.

After highlighting the impact of density on network performance, it is important to study the impact of gateway placement strategy. The results presented in the previous section highlight the significant impact of gateway placement on the communication reliability and energy efficiency of LoRaWAN systems dedicated to forest fire monitoring.

Although random gateway deployment may offer acceptable performance in low-density network scenarios, its limitations become clear as node density and traffic load increase.

The deterioration in PDR observed in the case of random deployment, particularly for short transmission intervals and a large number of sensor nodes, is mainly due to an unbalanced distribution of traffic and an increase in collisions. In large forest environments, random placement of gateways can result in poorly covered areas and overloading of certain gateways, which directly affects communication reliability. These limitations are critical in forest fire detection applications, where fast and reliable data transmission is essential for early detection and effective response.

Conversely, optimized gateway deployment based on the K-Means clustering algorithm significantly improves PDR by ensuring a more balanced spatial distribution of sensor nodes between gateways. By positioning gateways close to node density centers, the proposed solution reduces communication distances, limits channel congestion, and improves overall network robustness. This improvement is particularly noticeable in high-density scenarios, demonstrating the proposed method's ability to adapt to large-scale deployments.

From an energy perspective, the results show that increasing the transmission interval leads to a decrease in total and average energy consumption per node, regardless of the deployment strategy. This behavior is expected, as a longer interval reduces the number of transmissions performed over a given period. However, for identical network configurations, optimized deployment consistently leads to lower energy consumption than random deployment. This energy saving is due to better radio link quality, made possible by more judicious positioning of gateways.

The combination of high PDR and low energy consumption is particularly relevant for large-scale forest fire monitoring systems, where sensor nodes are typically battery-powered and deployed in remote areas. Optimized gateway placement thus not only helps extend network lifetime, but also ensures reliable transmission of critical data in emergency situations. These results confirm that optimizing gateway placement is a key lever for designing efficient, reliable LoRaWAN infrastructures that are well- suited to environmental monitoring and forest fire prevention applications.

6. CONCLUSIONS

This study provided an improved design and deployment approach for an IoT-based LoRaWAN system aimed at forest fire prevention and early detection. The work aims to improve communication dependability, energy efficiency, and spatial coverage in large-scale forest environments with tough terrain and inadequate infrastructure. The framework consists of three main components: a modeled representation of Chettaba Forest, Algeria, based on geographical data, a clustering-based optimization using the K-Means algorithm to determine optimal LoRaWAN gateway locations, and a comprehensive NS-3.45 simulation to evaluate network performance under different scenarios. These findings demonstrate that the suggested LoRaWAN-based architecture can be a crucial component of real-time fire detection and prevention systems. Additionally, reproducibility is guaranteed, and interaction with upcoming optimization algorithms is made easier by the use of open-source simulation tools like NS-3.45.

More broadly, this work provides a simulation-based framework for evaluating LoRaWAN gateway placement in forest environments. Other IoT applications like smart agriculture, animal monitoring, and disaster management can also benefit from the suggested methods. Even if the present findings are encouraging, there are still a number of unexplored study avenues that will be investigated in subsequent studies: Multi-objective Optimization: In order to simultaneously maximize coverage, decrease energy consumption, and reduce communication delay, the next stage will concentrate on integrating multi-objective optimization methods, such as Non-dominated Sorting Genetic Algorithm II (NSGA-II) or Multiobjective Evolutionary Algorithm Based on Decomposition (MOEA/D). This method will enable LoRaWAN networks to be configured in a more adaptable and balanced manner in dynamic environmental situations. Integration of Geographic Information Systems (GIS): Future work will investigate the integration of remote sensing and GIS data into the network deployment strategy. In particular, dynamically updated fire-risk maps based on environmental factors could be incorporated into the spatial distribution of sensor nodes and gateway placement, allowing network resources to be adapted according to varying fire-risk conditions. This extension would provide a more risk-aware deployment strategy while combining environmental information with communication-network optimization. Real Deployment and Field Experiments: A future objective is to move from simulation to real-world deployment using commercial LoRa modules and gateways in collaboration with local forestry services. Experimental validation will help to assess the real communication range, energy consumption, and detection latency in the field.

REFERENCES

[1] Pushpa, B., Kamarasan, M. (2018). Survey of various forest fire detection algorithm in image processing and remote sensing applications. International Journal of Emerging Technologies and Innovative Research, 5(7): 844-856. https://www.jetir.org/papers/JETIR180Z018.pdf.

[2] Üremek, İ., Leahy, P., Popovici, E. (2024). A system for efficient detection of forest fires through low power environmental data monitoring and AI. Engineering Proceedings, 68(1): 38. https://doi.org/10.3390/engproc2024068038

[3] Sairi, A., Labed, S., Miles, B., Kout, A. (2023). A review on early forest fire detection using IoT-enabled WSN. In 2023 International Conference on Advances in Electronics, Control and Communication Systems (ICAECCS), BLIDA, Algeria, pp. 1-6. https://doi.org/10.1109/ICAECCS56710.2023.10104887

[4] Sairi, A., Labed, S., Miles, B. (2025). Advancements in intelligent technologies approaches for forest fire detection: A comparative study. European Journal of Forest Engineering, 11(1): 66-80. https://doi.org/10.33904/ejfe.1482838

[5] Labed, S., Touati, H., Herida, A., Kerbab, S., Sairi, A. (2023). An AI-based image recognition system for early detection of forest and field fires. European Journal of Forest Engineering, 9(2): 48-56. https://doi.org/10.33904/ejfe.1322396

[6] Kufakunesu, R., Hancke, G.P., Abu-Mahfouz, A.M. (2020). A survey on adaptive data rate optimization in LoRaWAN: Recent solutions and major challenges. Sensors, 20(18): 5044. https://doi.org/10.3390/s20185044

[7] Diane, A., Diallo, O., Ndoye, E.H.M. (2025). A systematic and comprehensive review on low power wide area network: Characteristics, architecture, applications and research challenges. Discover Internet of Things, 5: 7. https://doi.org/10.1007/s43926-025-00097-6

[8] Brunel, G., Moinard, S., Ducanchez, A., Crestey, T., Pichon, L., Tisseyre, B. (2021). Empirical mapping for evaluating an LPWAN (LoRa) wireless network sensor

prior to installation in a vineyard. OENO One, 55(2): 301-313. https://doi.org/10.20870/oeno-one.2021.55.2.3102

[9] Miles, B., Bourennane, E.-B., Boucherkha, S., Chikhi, S. (2020). A study of LoRaWAN protocol performance for IoT applications in smart agriculture. Computer Communications, 164: 148-157. https://doi.org/10.1016/j.comcom.2020.10.009

[10] Centenaro, M., Vangelista, L., Zanella, A., Zorzi, M. (2016). Long-range communications in unlicensed bands: The rising stars in the IoT and smart city scenarios. IEEE Wireless Communications, 23(5): 60-67. https://doi.org/10.1109/MWC.2016.7721743

[11] Raza, U., Kulkarni, P., Sooriyabandara, M. (2017). Low power wide area networks: An overview. IEEE Communications Surveys & Tutorials, 19(2): 855-873. https://doi.org/10.1109/COMST.2017.2652320

[12] Augustin, A., Yi, J., Clausen, T., Townsley, W.M. (2016). A study of LoRa: Long range & low power networks for the Internet of Things. Sensors, 16(9): 1466. https://doi.org/10.3390/s16091466

[13] Mikhaylov, K., Petäjäjärvi, J., Hänninen, T. (2016). Analysis of capacity and scalability of the LoRa low power wide area network technology. In European Wireless 2016; 22th European Wireless Conference, Oulu, Finland, pp. 119-124. https://ieeexplore.ieee.org/document/7499263.

[14] Mekki, K., Bajic, E., Chaxel, F., Meyer, F. (2019). A comparative study of LPWAN technologies for large-scale IoT deployment. ICT Express, 5: 1-7. https://doi.org/10.1016/j.icte.2017.12.005

[15] Ratasuk, R., Vejlgaard, B., Mangalvedhe, N., Ghosh, A. (2016). NB-IoT system for M2M communication. In 2016 IEEE Wireless Communications and Networking Conference, Doha, Qatar, pp. 1-5. https://doi.org/10.1109/WCNC.2016.7564708

[16] Sinha, R.S., Wei, Y.Q., Hwang, S.H. (2017). A survey on LPWA technology: LoRa and NB-IoT. ICT Express, 3: 14-21. https://doi.org/10.1016/j.icte.2017.03.004

[17] Gaitan, N.C., Hojbota, P. (2020). Forest fire detection system using LoRa technology. International Journal of Advanced Computer Science and Applications, 11(5): 18-21. https://doi.org/10.14569/IJACSA.2020.0110503

[18] Vega-Rodríguez, R., Sendra, S., Lloret, J., Romero-Díaz, P., Garcia-Navas, J.L. (2019). Low cost LoRa based network for forest fire detection. In 2019 Sixth International Conference on Internet of Things: Systems, Management and Security (IOTSMS), Granada, Spain, pp. 177-184. https://doi.org/10.1109/IOTSMS48152.2019.8939193

[19] LoRa Alliance. (2020). TS001-1.0.4 LoRaWAN® L2 1.0.4 specification. Technical Report, LoRa Alliance. https://resources.lora-alliance.org/technical-specifications/ts001-1-0-4-lorawan-l2-1-0-4-specification.

[20] Jain, A.K. (2010). Data clustering: 50 years beyond K-means. Pattern Recognition Letters, 31(8): 651-666. https://doi.org/10.1016/j.patrec.2009.09.011

[21] MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. In Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, pp. 281-297.

[22] Ester, M., Kriegel, H.P., Sander, J., Xu, X.W. (1996). A density-based algorithm for discovering clusters in large spatial databases with noise. In Proceedings of the Second International Conference on Knowledge Discovery and Data Mining, Portland, Oregon, pp. 226-231. https://dl.acm.org/doi/10.5555/3001460.3001507.

[23] Kaufman, L., Rousseeuw, P.J. (1990). Finding Groups in Data: An Introduction to Cluster Analysis. John Wiley & Sons. https://doi.org/10.1002/9780470316801

[24] Ng, A.Y., Jordan, M.I., Weiss, Y. (2001). On spectral clustering: Analysis and an algorithm. In Proceedings of the 15th International Conference on Neural Information Processing Systems: Natural and Synthetic, Vancouver, British Columbia, Canada, pp. 849-856. https://dl.acm.org/doi/10.5555/2980539.2980649.

[25] Fraley, C., Raftery, A.E. (2002). Model-based clustering, discriminant analysis, and density estimation. Journal of the American Statistical Association, 97(458): 611-631. https://doi.org/10.1198/016214502760047131

[26] Ikotun, A.M., Ezugwu, A.E., Abualigah, L., Abuhaija, B., Heming, J. (2023). K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data. Information Sciences, 622: 178-210. https://doi.org/10.1016/j.ins.2022.11.139

[27] Loh, F., Mehling, N., Geißler, S., Hoßfeld, T. (2023). Efficient graph-based gateway placement for large-scale LoRaWAN deployments. Computer Communications, 204: 11-23. https://doi.org/10.1016/j.comcom.2023.03.015

[28] Can, B., Uyanik, H., Ovatman, T. (2023). Gateway placement in LoRaWAN enabled sensor networks. In Proceedings of the 12th International Conference on Sensor Networks - SENSORNETS, pp. 93-100. https://doi.org/10.5220/0011777000003399

[29] Mukhia, R., Sarambage Jayarathna, K.G., Lertsinsrubtavee, A. (2023). Performance evaluation of LoRaWAN forest fire monitoring network in the wild. In Proceedings of the 18th Asian Internet Engineering Conference, Hanoi, Vietnam, pp. 96-104. https://doi.org/10.1145/3630590.3630602

[30] Correia, F.P., da Silva, S.R., de Carvalho, F.B.S., de Alencar, M.S., Assis, K.D.R., Bacurau, R.M. (2023). LoRaWAN gateway placement in smart agriculture: An analysis of clustering algorithms and performance metrics. Energies, 16(5): 2356. https://doi.org/10.3390/en16052356

[31] Abreu, P.F.F., Mendes, L.H.D.O., Neto, G.A.S., et al. (2024). LoRaWISEP+: A comprehensive tool for strategic gateway placement in LoRaWAN networks. In: Simpósio Brasileiro de Engenharia de Sistemas Computacionais (SBESC), pp. 17-20. https://doi.org/10.5753/sbesc_estendido.2024.243700

[32] Etaati, A., Bastam, M., Ataie, E. (2024). Smart forest monitoring: A novel Internet of Things framework with shortest path routing for sustainable environmental management. IET Networks, 13(5-6): 528-545. https://doi.org/10.1049/ntw2.12135

[33] da Silva, C.N., de Abreu, P.F.F., da Silveira, J.D.F., dos Reis, J.V. (2022). Estimating the number of gateways through placement strategies in a LoRaWAN network. In 2022 XII Brazilian Symposium on Computing Systems Engineering (SBESC), Fortaleza/CE, Brazil, pp. 1-6. https://doi.org/10.1109/SBESC56799.2022.9964620

[34] Matni, N., Moraes, J., Oliveira, H., Rosário, D., Cerqueira, E. (2020). LoRaWAN gateway placement model for dynamic Internet of Things scenarios. Sensors,

20(15): 4336. https://doi.org/10.3390/s20154336
[35] Cruz, H.A.O., Ferreira, S.C.B., Araújo, J.P.L., et al. (2022). Methodology for LoRa gateway placement based on bio-inspired algorithms for a smart campus in wooded area. Sensors, 22(17): 6492. https://doi.org/10.3390/s22176492
[36] Modesto, C., Mozart, L., Gonçalves, G., Nahum, C., Castro, B., Klautau, A. (2026). LoRaWAN gateway placement for network planning using ray tracing-based channel models. IEEE Open Journal of the Communications Society, 7: 6612-6624. https://doi.org/10.1109/OJCOMS.2026.3704345
[37] Mhatre, J., Lee, A., Lee, H., Nguyen, T.N., Suo, K. (2024). Improving energy efficiency and reliability by optimizing gateway placement in dense LoRaWAN networks. In 2024 IEEE 10th World Forum on Internet of Things (WF-IoT), Ottawa, ON, Canada, pp. 340-345. https://doi.org/10.1109/WF-IoT62078.2024.10811389
[38] Bhatnagar, K.V., Kushwah, R. (2025). Evaluating gateway placement optimization algorithms for enhanced coverage and energy efficiency in LoRaWAN. In 2025 Seventeenth International Conference on Contemporary Computing (IC3), Noida, India, pp. 1-6. https://doi.org/10.1109/IC366947.2025.11290552
[39] Savithi, C., Kaewta, C. (2024). Multi-objective optimization of gateway location selection in long-range wide area networks: A tradeoff analysis between system costs and bitrate maximization. Journal of Sensor and Actuator Networks, 13(1): 3. https://doi.org/10.3390/jsan13010003
[40] Thepphaeng, S., Pirak, C. (2026). Optimal LoRaWAN gateway deployment for advanced metering infrastructure: A greedy capacity-coverage approach with Class-C bidirectional capacity analysis. Energies, 19(16): 3816. https://doi.org/10.3390/en19163816
[41] Nugroho, A.K., Yun, D., Lin, J.W., Kim, T. (2026). Joint optimization of gateway placement, resource configuration, and uplink scheduling for LoRaWAN bridge health monitoring. IEEE Access, 14: 53760-53798. https://doi.org/10.1109/ACCESS.2026.3681393
[42] Zerrouki, A., Kara, K., Rached-Kanouni, M., Redjaimia, L., Touafchia, B. (2024). Contribution to the study of the health state of holm oak in the Chettaba Forest (Algeria). Ecological Engineering & Environmental Technology, 25(2): 17-30. https://doi.org/10.12912/27197050/174219
[43] Soualah, L., Bouzekri, A., Chenchouni, H. (2024). Hoping the best, expecting the worst: Forecasting forest fire risk in Algeria using fuzzy logic and GIS. Trees, Forests and People, 17: 100614. https://doi.org/10.1016/j.tfp.2024.100614
[44] Abdelghany, A., Uguen, B., Moy, C., Lemur, D. (2021). Modelling of the packet delivery rate in an actual LoRaWAN network. Electronics Letters, 57(11): 460-462. https://doi.org/10.1049/ell2.12165
[45] Eiras, F.C.d.S., Zucchi, W.L. (2020). A statistical method for area coverage estimation and loss probability analysis on mobile sensor networks. Proceedings, 42(1): 27. https://doi.org/10.3390/ecsa-6-06531
[46] Liu, B.Y., Brass, P., Dousse, O., Nain, P., Towsley, D. (2005). Mobility improves coverage of sensor networks. In Proceedings of the 6th ACM International Symposium on Mobile ad Hoc Networking and Computing, Urbana-Champaign, IL, USA, pp. 300-308. https://doi.org/10.1145/1062689.1062728
[47] Farsi, M., Elhosseini, M.A., Badawy, M., Ali, H.A., Eldin, H.Z. (2019). Deployment techniques in wireless sensor networks, coverage and connectivity: A survey. IEEE Access, 7: 28940-28954. https://doi.org/10.1109/ACCESS.2019.2902072
[48] Adelantado, F., Vilajosana, X., Tuset-Peiro, P., Martinez, B., Melia-Segui, J., Watteyne, T. (2017). Understanding the limits of LoRaWAN. IEEE Communications Magazine, 55(9): 34-40. https://doi.org/10.1109/MCOM.2017.1600613
[49] Magrin, D., Centenaro, M., Vangelista, L. (2017). Performance evaluation of LoRa networks in a smart city scenario. In 2017 IEEE International Conference on Communications (ICC), Paris, France, pp. 1-7. https://doi.org/10.1109/ICC.2017.7996384