LoRaWISEP+: A Comprehensive Tool for Strategic Gateway Placement in LoRaWAN Networks

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***Abstract*—The Internet of Things has revolutionized device interconnectivity, with Low Power Wide Area Networks (LPWAN) enabling long-range communication with minimal energy consumption. Within this context, LoRaWAN is widely recognized as an efficient and robust technology for LPWAN networks. However, strategic gateway deployment remains a challenging for optimizing network performance. In this way, this paper issue proposes LoRaWISEP+, an enhanced version of the LoRaWISEP system, consisting of a comprehensive tool designed to improve the deployment process of LoRaWAN gateways. This solution incorporates additional clustering algorithms, such as K-Medoids (KMD) and Fuzzy C-Means (FCM), and a redesigned user-friendly interface, facilitating optimal placement of gateways and improving overall network coverage and reliability. In order to validate the new features of the proposed tool, a thorough evaluation was conducted using real-world deployment scenarios. Results demonstrate that different clustering algorithms exhibit strengths in specific characteristics, such as FCM being more suitable for lower energy consumption and K-Means (KM) being more suitable for higher transmission rates. This makes LoRAWISEP+ an enabling tool for optimizing network planning according to the most beneficial characteristic for the user.**

***Index Terms*—Clustering, IoT, LoRaWAN, Placement, Tool**

I. Introduction

The Internet of Things (IoT) is a transformative technology that enhances device interconnectivity, facilitating data exchange across sectors like smart cities, healthcare, and industrial automation [1]. Among the communication technologies supporting IoT, Low-Power Wide-Area Networks (LPWANs) stand out for their long-range communication and low energy consumption, making them ideal for battery-powered devices in remote areas. LoRaWAN, a leading LPWAN specification, operates in the unlicensed spectrum, offering secure, bidirectional communication with low data rates over large distances [2]. Its architecture, comprising End Devices (EDs), Gateways (GWs), Network Server (NS), and Application Server (AS), ensures reliable, energy-efficient communication for IoT applications [3].

A key aspect of LoRaWAN network planning is optimizing the number and placement of GWs, which directly affects coverage, performance, and cost. This requires advanced tools to handle complex environments and device distributions [4]. The initial LoRaWISEP tool addressed this by using clustering and genetic algorithms for optimal GW placement but faced limitations in real-world applicability and user interaction [5].

This paper introduces LoRaWISEP+ [1], an enhanced version of LoRaWISEP, incorporating new input parameters and clustering algorithms like Fuzzy C-Means and K-Medoids [6]. These improvements enable more efficient gateway placement, offering better coverage and energy efficiency than traditional grid-based methods.

The remainder of this paper is organized as follows. Section II discusses related works in the field of LoRaWAN network planning and optimization. Section III provides a detailed system overview of LoRaWISEP+, highlighting the new features and improvements over the previous version. Section IV outlines the evaluation methodology, describing the enhanced simulation capabilities and the performance metrics used to assess the effectiveness of the clustering algorithms. In Section V, results from the simulations are presented and discussed, analyzing the performance impacts of each clustering algorithm on the network. Finally, some conclusions and further considerations are presented in Section VI.

II. Related Work

Several tools and methodologies have been developed to address the challenges associated with LoRaWAN network planning, each one offering unique features and approaches. These solutions range from simulation tools that evaluate network performance [7], [8] or gateway placement [4], [5], [9] to algorithms that optimize network configurations based on various metrics [10]. However, many of these tools lack comprehensive optimization capabilities and user-friendly interfaces, essential for practical application. Given these gaps in functionality and usability, Table I provides a concise summary of the key characteristics and limitations of the discussed related works.

In [11], LoRaPlan addresses message collisions in LoRaWAN networks by evaluating gateway placement and collision probabilities. However, it relies on manual gateway placement and lacks optimization algorithms. LoRaWISEP+ improves this by automating placement and integrating advanced optimization techniques, providing a more scalable solution.

[1]https://github.com/LITTORAL-LAB/LoRaWISEP-desktop.git

TABLE I
SUMMARY OF RELATED WORKS ON LORAWAN NETWORK PLANNING

Ref.	Solution Features
[7]	LoRaWANSim: MATLAB-based simulator for PHY/MAC layers, network behavior, and performance metrics.
[8]	LoRaCity: Simulates network configurations in urban areas; evaluates performance.
[9]	DPLACE: Optimizes gateway positioning using K-means and FCM algorithms.
[10]	LoRaDRL: Deep reinforcement learning for parameter optimization in LoRaWAN.
[11]	LoRaPlan: Analyzes gateway placement and collision probabilities.
[12]	Smart city metering: Algorithm for optimal gateway deployment based on geographic data.
[13]	Network deployment: Framework for analyzing network models, lifespan, and interference.

The study in [13] recommends LoRaWAN deployment strategies focusing on network lifetime, latency, and interference. While comprehensive, it lacks advanced optimization tools like genetic or clustering algorithms, which could enhance planning efficiency. LoRaWISEP+ addresses this gap with its integrated optimization techniques.

Similarly, [12] focuses on energy-efficient metering network planning for smart cities using LoRaWAN, but lacks a user-friendly simulation interface and advanced optimization. LoRaWISEP+ offers these features, integrating optimization methods into an intuitive environment.

In [9], DPLACE uses K-means and FCM for dynamic gateway positioning, but lacks interaction capabilities and evolutionary algorithms. LoRaWISEP+ overcomes this with its interactive SaaS platform, combining clustering and evolutionary algorithms.

Although previous studies provide useful insights, they often lack comprehensive optimization and user-friendly interfaces. LoRaWISEP+ stands out by combining advanced optimization with a user-focused design for effective LoRaWAN network planning.

III. LORAWISEP+: SYSTEM OVERVIEW

LoRaWISEP+ introduces several key features aimed at providing a more comprehensive and adaptable solution for LoRaWAN network planning. The system is designed to operate as a standalone desktop application, which aims to ensure a robust and platform-independent user experience. This section provides an overview of the architecture, user interface enhancements, and new simulation capabilities introduced in LoRaWISEP+.

A. Software Architecture

LoRaWISEP+ transitions from a cloud-based model to a desktop application, offering greater control over data and removing the need for continuous internet connectivity. Built with Electron-Vite [2], the system integrates with native desktop features, ensuring optimized performance and accessibility. The architecture is modular, with distinct layers for the user interface, simulation processing, and data management, facilitating easy updates and maintenance.

LoRaWISEP+ optimizes gateway distribution in LoRaWAN networks using simulations and machine learning techniques. Input parameters include the number of devices (EDs), packet length, shadowing model, spreading factor, and transmission power, which influence traffic, energy consumption, and coverage, enabling network performance optimization [14].

The system uses Network Simulator 3 (NS-3)[3] to simulate network performance, generating metrics such as packet delivery ratio, signal-to-noise ratio, delay, and energy consumption. These metrics are analyzed by machine learning algorithms to optimize gateway placement, enhancing network coverage and efficiency.

Finally, simulation results and optimized configurations are stored in a cloud-based database, allowing large-scale data analysis and continuous system improvement.

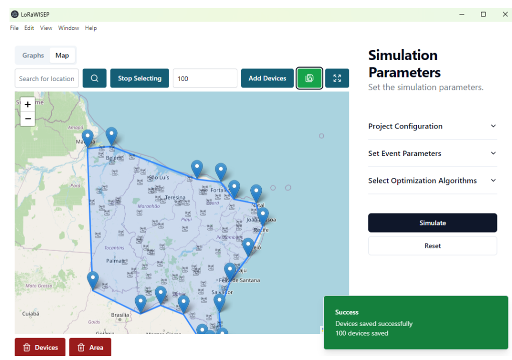


Fig. 1. User Interface Enhancements.

B. User Interface Enhancements

The user interface of LoRaWISEP+ has been redesigned to provide an intuitive and responsive experience, illustrated in Figure 1. Key improvements include:

- *Real-World Map Integration*: Users can now select real-world locations directly on an interactive map, simplifying the process of setting up simulation scenarios.
- *Advanced Configuration Options*: Enhanced configuration panels allow users to easily adjust simulation parameters such as device density, transmission power, and environmental factors.
- *Dynamic Simulation Feedback*: The interface provides real-time feedback during simulations, displaying key metrics and graphical representations of network coverage and performance.

C. Simulation Capabilities

LoRaWISEP+ has enhanced its simulation framework by incorporating additional inputs such as packet size, transmission intervals, and simulation duration, allowing for more accurate modeling of complex network scenarios.

[2]https://electron-vite.org

[3]https://www.nsnam.org

Previously, K-Means (KM) and Genetic algorithms were used for gateway placement. KM, which clusters gateways at centroids, improved coverage but struggled in dynamic environments [4]. Although powerful, the Genetic algorithm required substantial computational resources, making it less practical for current use [5].

The new version integrates more robust algorithms like FCM and KMD. FCM is ideal for environments with fluctuating conditions, as it adapts to dynamic networks using probabilistic clusters, enhancing flexibility and responsiveness [15]. KMD, suitable for dense urban areas, minimizes distances between gateways and devices, improving signal quality and reducing latency [16].

These advancements make LoRaWISEP+ a valuable tool for optimizing LoRaWAN networks, equipping users with precise control over network architecture to suit specific operational contexts.

IV. Evaluation Methodology

The latest version of LoRaWISEP+ integrates clustering algorithms to optimize gateway placement in urban LoRaWAN networks. This section details the methodology used to evaluate these algorithms and their impact on network performance.

Building on the previous framework, which simulated urban deployments considering parameters such as IoT device density, area dimensions, and urban obstacles, the new version incorporates FCM and KMD clustering algorithms. These algorithms enhance gateway placement by accounting for urban obstacles like buildings, represented in a grid layout with adjustable parameters for size and spacing.

Using the Elbow method, 16 gateways were selected for the simulation, as detailed in Table II, ensuring optimal coverage and capacity. Results were averaged over 33 trials with different random seeds for robustness. This methodology prevents redundancy and overlap in gateway distribution, improving traffic management.

TABLE II
Simulation Parameters

Parameters	Values
IoT devices	1000
Length of the area	1000 m
Width of the area	1000 m
Packet size	20 bytes
Simulation time	1200s
Periodic transmission interval	600s
Obstacle profile	Urban
Heuristic for GWs selection	*Elbow*

Additionally, a GRID layout [9] with uniformly distributed gateways serves as a baseline for comparison. This allows a clear evaluation of how clustering algorithms outperform basic uniform distribution in optimizing gateway placement.

Simulating different urban layouts and obstacles [9] evaluates the algorithms adaptability, ensuring LoRaWISEP+ remains a cutting-edge tool for optimizing LoRaWAN deployments in diverse environments.

V. Results and Discussion

This section discusses the performance of the LoRaWISEP+, focusing on the impact of different clustering algorithms on key network metrics: SNR, Delay, Energy Consumption, PDR, and RSSI.

Figure 2(a) shows that KM and KMD achieve higher SNR values compared to FCM and the Grid method, suggesting better signal clarity under these algorithms. However, the KM method, while showing lower SNR, results in a lower delay, see Figure 2(b), among the strategies, potentially offering faster data transmission in less complex network scenarios.

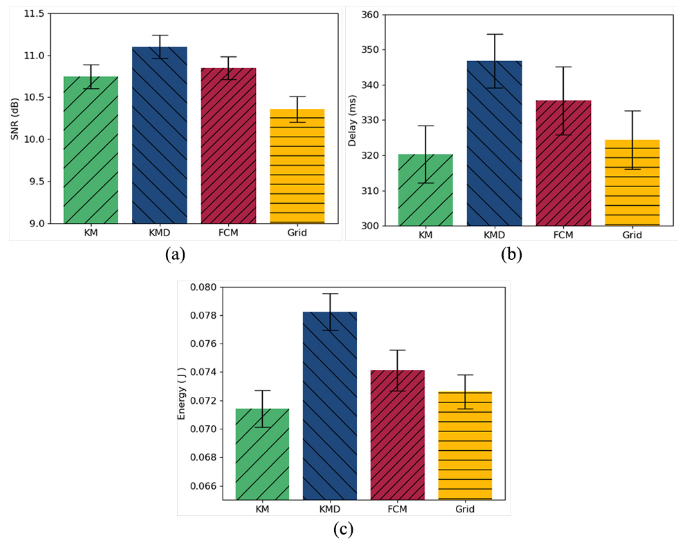
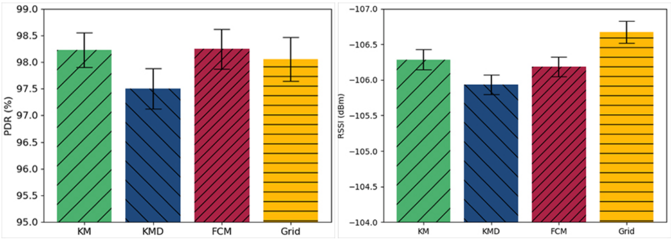


Fig. 2. Comparison of SNR and Delay across different clustering algorithms.

Energy efficiency is critical in IoT networks to extend the lifetime of battery-dependent devices. In this regard, as shown in Figure 2(c), KM demonstrates the lowest energy consumption, which is beneficial for long-term deployments without frequent maintenance. Conversely, KMD, while slightly less efficient than KM, still outperforms FCM and the traditional Grid approaches in SNR.

With regard to PDR and RSSI, all algorithms maintain a relatively high PDR, Figure 3(a), indicating robust network reliability. However, KMD demonstrates a slightly lower PDR compared to the other algorithms, which may be due to its less effective gateway placement in high-density areas. In terms of RSSI, KM, KMD and FCM provide stronger signals compared to Grid, see Figure 3(b), corroborating the SNR findings that these algorithms are more effective in managing interference and ensuring signal strength.

The results indicate that FCM and KMD generally offer superior performance in terms of SNR and RSSI. However, the traditional Grid method, while providing lower delay, offers a valuable balance between time of convergence and other performance metrics. Consequently, the choice of algorithm should be guided by the specific requirements of the deployment scenario, considering factors such as the need for optimal signal clarity and energy efficiency. This approach



(a) (b)

Fig. 3. PDR and RSSI performance for various clustering algorithms.

allows network planners to tailor the network configuration effectively to the specific demands of the environment and operational objectives.

Furthermore, the slightly higher energy consumption and delay observed in FCM could be attributed to its adaptability in dynamic environments, where network conditions frequently fluctuate. This feature renders it a suitable choice for urban areas characterized by highly variable environmental factors. Table III provides an overview of the algorithms discussed and their strengths as observed in the LoRaWISEP+ evaluation.

TABLE III
SUMMARY OF ALGORITHM STRENGTHS IN LORAWISEP+ EVALUATION.

Strength	**KM**	**KMD**	**FCM**	**Grid**
Higher transmission rate	✓		✓	
Lower energy consumption	✓		✓	✓
Stronger transmission signal	✓	✓	✓	
Better adaptability in dynamic environments			✓	✓

Overall, the integration of clustering algorithms in LoRaWISEP+ significantly enhances network performance across various metrics, providing flexible options to optimize LoRaWAN deployments based on specific environmental and operational needs.

VI. CONCLUSION

This study has evaluated the updated LoRaWISEP+ system, which incorporates clustering algorithms to optimize LoRaWAN network performance. The integration of KM and KMD has shown to enhance signal clarity and network connectivity, proving highly effective in environments with substantial interference. Although the Grid method exhibited higher delay times compared to KM, its application could still be particularly beneficial in scenarios demanding swift data transmission. On the other hand, FCM demonstrated versatility in dynamic environments, adapting effectively to fluctuating network conditions due to its probabilistic clustering approach.

Despite these advancements, LoRaWISEP+ has limitations. Energy consumption trade-offs and varying performance in different urban layouts suggest no one-size-fits-all solution. These findings highlight the importance of selecting a clustering algorithm that aligns with specific operational requirements and environmental conditions.

LoRaWISEP+ aids in achieving better planning, providing a sophisticated toolkit for customizing LoRaWAN deployments. As future directions, researches should explore the scalability of these algorithms in larger, more diverse networks and investigate the integration of predictive machine learning models to optimize network configurations in real-time.

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