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Optimizing LoRa Gateway Placement for Marine Buoy Monitoring Using Particle Swarm Optimization (PSO)

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ABSTRACT

Effective marine environmental monitoring is critical for ensuring navigational safety, with LoRa technology emerging as a promising solution due to its long-range, low-power capabilities. However, the performance of LoRa networks heavily depends on strategic gateway placement, a task often performed manually, leading to suboptimal coverage. This study addresses this challenge by implementing and validating a Particle Swarm Optimization (PSO) algorithm to determine the optimal placement of gateways for a real-world network of 157 marine buoys in the Madura Strait. The PSO algorithm, configured with 30 particles and 100 iterations, was benchmarked against a baseline manual selection method based on geographic centrality. Results demonstrate a significant performance gain: the PSO-optimized configuration achieved 100% network coverage (157 buoys), a 34.2% increase over the 117 buoys covered by the manual method. These findings confirm that employing PSO for gateway placement substantially enhances network efficiency and data reliability, highlighting its value for creating robust and scalable marine IoT applications.

I. INTRODUCTION

Development of information technology is increasingly affecting various sectors, including monitoring systems in the marine environment that play an important role in maintaining the safety of navigation and the aquatic environment. In marine monitoring systems, the use of technology that is power-efficient but capable of covering long distances is necessary. LoRa (Long Range) is a wireless communication technology that can answer these needs with long-range data transmission capabilities and low power consumption, enabling data transmission from sensor nodes at sea to gateways connected to land for real-time monitoring. The Particle Swarm Optimization (PSO) method is an optimization technique that is widely known in the search for optimal solutions, including for determining the best location for gateway placement in LoRa networks. It was first developed by Dr. R.C. Eberhart and Dr. James Kennedy, PSO is inspired by the natural behavior of flocks of animals such as birds and fish that seek optimal positions in their groups. In PSO, a number of "particles" or initial solutions randomly move in the search space and follow a regulated speed to reach the best solution location [1].

Previous studies have also shown the effectiveness of PSO in optimizing gateway placement in LoRa networks. In some cases, the modified PSO introduces a spacing mechanism between gateways at the initialization stage and particle movement during the iteration process, which accelerates convergence and produces more optimal results. This study found that modified PSO can compete with deterministic methods in more complex LoRa network structures, for example in square, triangular, or even more irregular shapes [2].

While LoRa is a suitable technology, its practical performance heavily relies on the strategic placement of gateways. In many deployments, gateway placement is often based on convenience or simple heuristics (e.g., selecting the nearest available high ground), which rarely yields optimal network coverage. This suboptimal placement can lead to significant data loss and reduced monitoring effectiveness, particularly in challenging maritime environments where signal propagation is complex. This highlights a critical research gap: the lack of quantitative validation for advanced optimization algorithms in the specific context of LoRa-based marine buoy monitoring.

To address this gap, this study employs the Particle Swarm Optimization (PSO) algorithm, a robust metaheuristic technique known for its excellence in solving complex, non-linear optimization problems. Inspired by the social behavior of animal swarms [9], PSO is well-suited for identifying optimal gateway locations by considering factors like device distance and potential coverage overlap. The novelty of this research lies not only in applying PSO to a maritime buoy context or a domain less explored than terrestrial LoRa applications, but also in quantitatively demonstrating its superiority over a conventional manual selection baseline. By doing so, this study provides concrete evidence of the significant network efficiency gains achievable through intelligent optimization.

II. Related Works

This research aims to improve the performance of monitoring systems using LoRa technology. The focus of this research is the development and use of a smart gateway that can manage data transmission using a simple LoRa protocol. This system utilizes a Raspberry Pi-based smart gateway to connect end devices with servers, collect sensor data, and measure QoS parameters such as throughput and packet loss. The research results show that the LoRa-based monitoring system with the SLP protocol can operate effectively in collecting sensor data and displaying it in real-time via a smart gateway. Analysis shows that although the throughput is quite stable, the throughput value obtained is lower compared to the LoRaWAN architecture due to the additional data entry process to the database and web services [4].

The paper by Kaur et al. investigates optimizing LoRa network perfomance for industrial settings using machine learning. It combines an Artificial Neural Network (ANN) with Particle Swarm Optimization (PSO) to maximize received power, addressing signal challenges in obstructive and non-obstructive indoor scenarios. Their approach significantly improves key metrics like signal-to-noise ratio, outage probability, and bit error rate. This work highlights LoRa's adaptability for Industrial IoT, showing potential to enhance connectivity and efficiency in demanding industrial environments [5].

A recent study explores the use of solar-powered LoRa sensor nodes for monitoring transmission tower tilt angles, a crucial factor in ensuring the reliability of power grids. Unlike traditional accelerometers, which are sensitive to vibrations caused by external forces such as wind, the study utilizes gyroscopes to measure tilt in dynamic conditions. To enhance the prediction accuracy of tilt angles, the authors introduce a sliding XGBoost predictor, which is efficient and eliminates the need for data normalization. In addition, the study applies Double Chain Chaos Particle Swarm Optimization (DCCPSO) to fine-tune the hyperparameters of the XGBoost model, ensuring faster convergence and higher prediction accuracy without falling into local optima. This combination of LoRa's long-range communication and advanced machine learning techniques demonstrates the potential for real-time, low-power monitoring systems in remote areas, ensuring reliable and scalable performance for transmission tower monitoring [6].

III. Methodology

A. Hardware System

The RFM98 LoRa module is a long-range, low-power communication device ideal for IoT applications, supporting up to several kilometers of range. It operates at frequencies between 433-470 MHz and offers high sensitivity (-148 dB) and error correction for stable data transmission. The module is suited for remote monitoring, like water quality systems. The NodeMCU ESP32 is an affordable, compact microcontroller with WiFi and Bluetooth. It features a 240 MHz processor, 18 ADC pins, and supports I2C, SPI, and serial communication. Its small size (58.6 x 29 mm) makes it ideal for IoT projects [7].

The Quectel LC86G GNSS module supports multiple satellite systems for accurate positioning with low power consumption, tracking up to 47 satellites. The LDR sensor measures light intensity by varying resistance, outputting digital or analog signals, used in light-sensitive applications. The 25V voltage sensor module reduces voltage for safe input to microcontrollers, detecting voltages from 0.02445V to 25V. The GY-521 MPU-6050 combines an accelerometer and gyroscope for motion sensing, operating at 3.3V–5V and using I2C for data transfer [8].

B. System Design

The system uses the NodeMCU ESP32 as the main microcontroller, which is equipped with a 32-bit Tensilica Xtensa LX6 microprocessor and integrated WiFi and Bluetooth communication modules. In addition, the ESP32 has internal RF components, including a power amplifier, low-noise receiver amplifier, antenna switch, and filter. The system also features a LoRa RFM98 module to enable long-distance data transmission up to 15 km with low power consumption, serving as a data communication medium between devices via the LoRa.

Quectel LC86G GNSS module is used in this system to obtain accurate location data by supporting several satellite constellations such as GPS, GLONASS, Galileo, and QZSS, thus enabling real-time position tracking. For monitoring the buoy's environmental conditions, the system is equipped with several additional sensors. The LDR (Light Dependent Resistor) light sensor module is used to detect the light intensity of the buoy lights, and the 25V voltage sensor module is used to monitor the battery voltage up to 25V. The system is also equipped with a GY-512 MPU-6050 module that combines an accelerometer and a gyroscope to measure angles in the x, y, and z axes simultaneously, allowing monitoring of the buoy's orientation. The DHT11 temperature sensor serves to measure the temperature inside the buoy, while the humidity sensor measures the humidity inside the buoy.

Figure 1 shows the workflow of the system. It starts from the integration of the source code on the NodeMCU ESP32 to manage data communication and buoy condition monitoring. Data obtained from sensors such as LDR, voltage, temperature, humidity, and location are sent and displayed on the website. The data is then sent through the LoRa network using the LoRa gateway, which is then received by the web server and data storage is carried out and then visualized through the website.

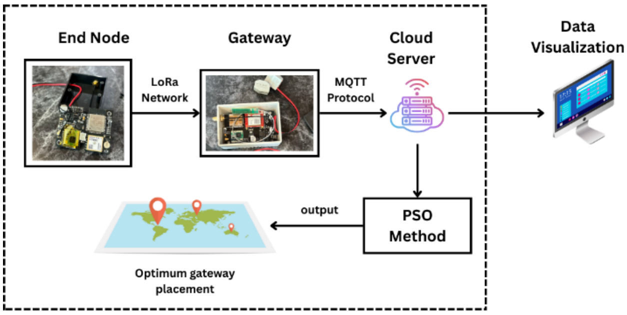


Figure 1. System model

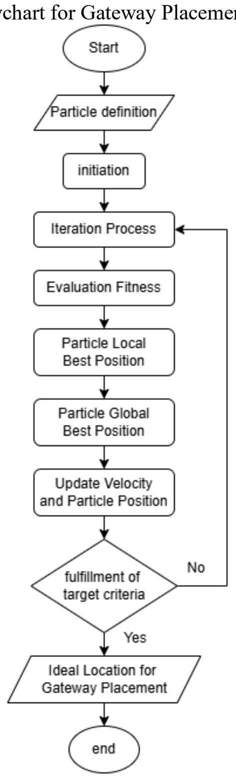
C. Gateway Placement Optimization

The central challenge addressed in this study is the optimal placement of LoRa gateways to maximize network coverage for the marine buoys. The problem is formulated as selecting a predetermined number of gateway locations from a larger set of candidates. To solve this, a fitness function was defined to evaluate the quality of any given solution, and the Particle Swarm Optimization (PSO) algorithm was employed to find the best possible configuration. A baseline manual selection method was also implemented to serve as a benchmark for performance comparison.

The primary objective of the optimization is to maximize the number of covered buoys. Therefore, the fitness of a potential solution of a specific combination of gateway locations is calculated based on the network's coverage rate. An end node (buoy) is considered "covered" if its distance to at least one of the active gateways is within the maximum effective communication range. This range was determined through field testing to be 4 kilometers, a distance at which a Received Signal Strength Indicator (RSSI) of -100 dBm or better was consistently maintained, indicating a reliable link.

Particle Swarm Optimization (PSO) was utilized as the primary optimization technique due to its proven effectiveness in solving complex, non-linear problems. Inspired by the collective behavior of animal swarms, the algorithm uses a population of "particles," where each particle represents a potential solution (a complete set of gateway locations). The algorithm iteratively seeks the optimal solution by updating the position and velocity of each particle based on its own best-known position and the best-known position of the entire swarm. The iterative workflow of this algorithm is visually summarized in Figure 2. The core of the algorithm relies on the following equations to guide the particle movement:

Figure 2. Flowchart for Gateway Placement Using PSO



Each particle in PSO represents a potential solution and possesses two main attributes: position and velocity. The position denotes the proposed solution, while the velocity determines the particle's movement within the search space [10].

The algorithm utilizes the best information achieved by each particle, as well as the best information from the entire swarm, to guide the movement toward the optimal solution. This iterative process aims to refine particle positions based on updated velocities, considering cognitive and social components. The fundamental equations for updating particle velocity and position are as follows:

$$v_i(t) = \omega \,.\, v_i(t-1) + c_1 \,.\, r_1 \,.\, (p_{bi} - x_i(t)) + c_2 \,.\, r_2 \,.\, (g_b - x_i(t)) \quad (1)$$

Where vi (t) represents the velocity of particle i at iteration t, ω is the inertia weight, c1 and c2 are coefficients for the cognitive and social influence, and r1 and r2 are random values between 0 and 1. Here, pbi is the best position achieved by the particle itself, and gb is the best position achieved by the entire swarm. The particle position is then updated using the equation:

$$x_i\,(t + 1) = x_i\,(t) + v_i\,(t + 1) \tag{2}$$

Where xi (t + 1) is the updated position of particle i at the next iteration. To validate the performance of the PSO algorithm, its results were compared against a baseline heuristic method that simulates a logical, manual approach to gateway placement. This "Manual Selection" method first calculates the geographic centroid (the average latitude and longitude) of all 157 buoy locations. It then identifies the pre-defined candidate locations that are physically closest to this central point and selects the required number of gateways from this subset. This baseline provides a robust benchmark to quantify the improvements achieved by the more advanced PSO technique.

D. Experimental Setup and Parameters

The experiment was designed to replicate a real-world operational scenario for marine monitoring. The test area was located in the Madura Strait, with buoy data collected along an approximately 16 km shipping lane to ensure the testbed was representative of a practical deployment environment. The dataset for this study comprised 157 unique end node locations and 25 potential candidate locations for gateway installation, providing a complex search space for the optimization algorithm. For this study, the optimization objective was to select the optimal placement for 3 gateways, a number determined by project scope and hardware constraints.

The configuration of the Particle Swarm Optimization (PSO) algorithm was carefully selected to ensure a thorough and efficient search of the solution space, balancing exploration of new areas with exploitation of known good solutions. The population size was set to 30 particles. This number is a well-established standard in PSO literature, providing sufficient diversity to explore the search space comprehensively without incurring excessive computational expense. The algorithm was run for 100 iterations, a duration determined to be sufficient for the algorithm to converge to a stable, optimal solution, as confirmed by the convergence graph where the gBest score shows no significant improvement in later iterations. The inertia weight (w) was set to 0.7, a value that effectively balances the algorithm's global and local search capabilities. Finally, the cognitive (c1) and social (c2) coefficients were both set to 1.5. This symmetrical weighting ensures a balanced influence between a particle's individual best-known position and the global best-known position of the entire swarm, which is crucial for preventing premature convergence on suboptimal solutions. Together, these parameters create a robust and replicable optimization process tailored for this gateway placement problem.

IV. Implementation Result and Discussion

This chapter presents the experimental results, beginning with a characterization of the test environment and the initial signal data. It then details the performance of the Particle Swarm Optimization (PSO) algorithm and provides a quantitative comparison against a baseline Manual Selection method. The discussion culminates in an analysis of the optimized gateway placement and its practical advantages.

A. Testbed and Initial Signal Characterization

The experiment was conducted in a real-world maritime environment in the Madura Strait, along a 16 km shipping lane frequented by marine traffic. This location was chosen to represent a typical operational scenario with realistic signal propagation challenges. Initial data collection was performed to establish a baseline understanding of the signal conditions in the area.

Figure 3. Initial Signal Characterization Based on RSSI Values in the Madura Strait Testbed

Figure 3 provides a spatial visualization of the raw Received Signal Strength Indicator (RSSI) data collected from the 157 buoys. The color gradient on the map represents the signal strength, ranging from stronger signals (yellow tones) to weaker signals (purple tones). The visualization reveals a significant variation in signal quality across the testbed, influenced by factors such as distance and environmental obstructions. This initial, non-optimized signal map highlights the clear necessity for a strategic approach to gateway placement to ensure consistent and reliable network coverage for all buoys.

B. PSO Algorithm Convergence and Optimization

Having established the baseline conditions, the Particle Swarm Optimization (PSO) algorithm was executed to find the optimal placement for three gateways.

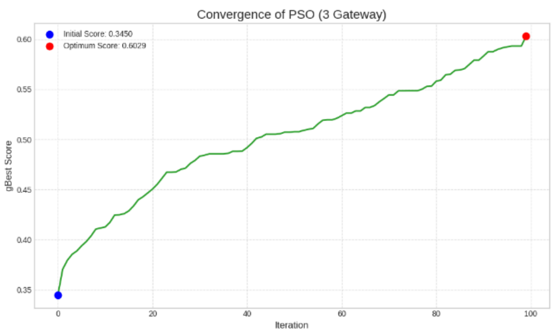


Figure 4. Convergence of PSO gBest Score over 100 Iterations

The convergence of the algorithm, depicted in Figure 4, demonstrates its effectiveness. The graph shows the progressive improvement of the global best (gBest) fitness score over 100 iterations. It begins with an average score from the initial random particle population and steadily increases, eventually stabilizing at a final optimal score of 0.6029. This convergence pattern indicates that the algorithm successfully explored the solution space and honed in on a high-quality solution without premature termination.

C. Comparative Analysis and Final Placement

The primary result of this study is the quantitative performance comparison between the PSO-optimized placement and the baseline Manual Selection method. As illustrated in the bar chart in Figure 5, the PSO approach yielded vastly superior results. The optimized configuration achieved 100% network coverage, successfully connecting to all 157 buoys. In contrast, the Manual Selection method only covered 117 buoys (74.5%), leaving 40 buoys without a connection. This equates to a 34.2% increase in network coverage provided by the PSO method over the baseline.

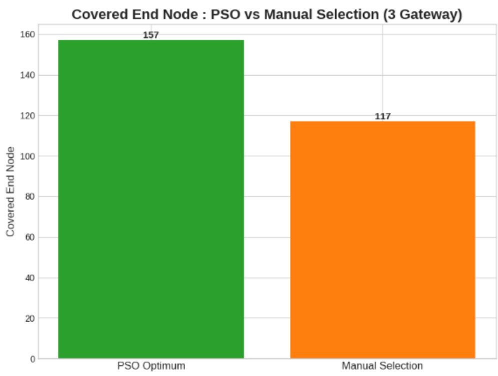


Figure 5. Network Coverage Comparison: PSO vs. Manual Selection

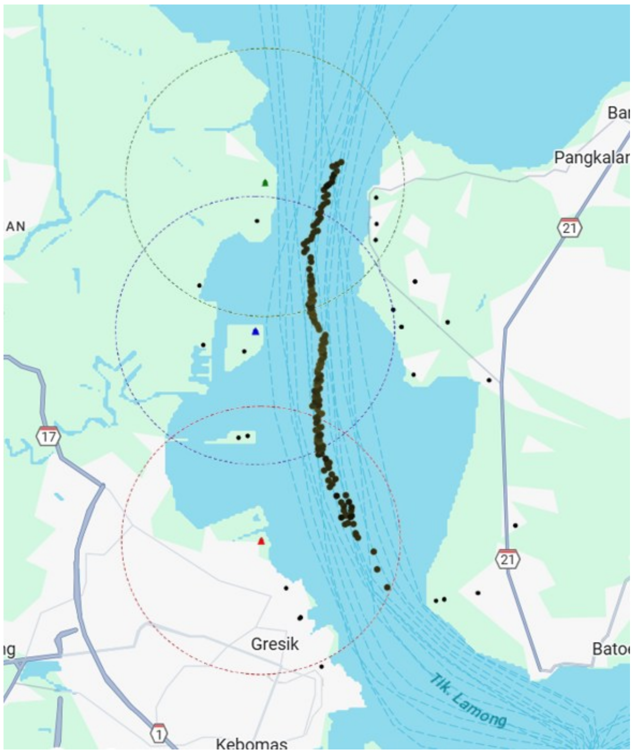


Figure 6. Optimal Gateway Placement and Coverage Area Determined by PSO

The strategic advantage of the PSO solution is visually evident in Figure 6, which illustrates the final optimized gateway placement within the operational test area. The map displays several key components of the experiment: the dense cluster of points in the sea represents the 157 end nodes (buoys) to be monitored, while the black dots on land indicate the 25 candidate locations available for gateway installation. These candidate sites were pre-selected based on practical criteria such as the availability of necessary infrastructure and site security. From these potential locations, the PSO algorithm selected the three optimal gateways, which are marked as distinct red, green, and blue triangles, each with its respective 4 km coverage radius shown as a dashed circle.

It is clear that the algorithm distributed these three gateways strategically along the elongated formation of the buoys. This placement creates an effective, overlapping coverage blanket that, as the analysis confirmed, successfully encompasses all end nodes within the network. This spatial distribution contrasts sharply with the likely outcome of the centroid-based manual method, which would presumably cluster the gateways in the geographic middle and fail to cover the extremities of the route. This visualization confirms that PSO can identify non-intuitive, spatially aware solutions that are critical for maximizing network reliability in real-world, non-uniform deployments.

V. CONCLUSION

This study successfully demonstrated the effectiveness and practical necessity of employing an advanced optimization algorithm for LoRa gateway placement in a real-world marine environmental monitoring system. The research set out to address the common practice of using manual or simple heuristic methods for gateway placement, which often result in suboptimal network performance. By implementing and validating the Particle Swarm Optimization (PSO) algorithm against a baseline Manual Selection method, this study has provided clear, quantitative evidence of the benefits of an intelligent optimization approach.

The key finding of this research is the significant superiority of the PSO-derived solution. The optimized gateway configuration achieved complete network coverage (100%), successfully connecting to all 157 marine buoys within the testbed. This stands in stark contrast to the baseline method, which only covered 74.5% of the buoys, representing a 34.2% increase in network coverage for the PSO method. This result empirically confirms that PSO can navigate the complex spatial trade-offs of a non-uniform environment like the Madura Strait to find a globally optimal solution that a simpler heuristic would miss. These findings underscore the critical impact of strategic network planning on data reliability and operational continuity for maritime safety applications.

The implications of this study are significant for the broader field of IoT deployments, particularly in challenging environments. It highlights that for critical infrastructure, relying on simplistic placement strategies is insufficient and can lead to significant gaps in data collection. The success of the PSO algorithm validates its use as a robust and scalable tool for LoRa network planning, capable of adapting to diverse geographical layouts to ensure maximum efficiency. While this study confirms the method's effectiveness, future work could expand upon this foundation by incorporating multi-objective fitness functions that also consider parameters such as gateway energy consumption or data latency. Furthermore, comparing PSO with other metaheuristic algorithms and applying the methodology to dynamic environments with mobile nodes could provide even deeper insights into optimizing large-scale IoT networks.

In conclusion, the integration of LoRa technology with Particle Swarm Optimization presents a powerful, scalable, and energy-efficient solution for advancing marine monitoring systems. This research paves the way for more reliable data-driven decision-making, ultimately enhancing safety and efficiency in maritime operations.

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