Proactive Wildlife Monitoring: Leveraging LoRa Technology to Prevent Human-Bear Conflicts in Romania

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***Abstract*— Wildlife monitoring has become increasingly vital in mitigating human-wildlife conflicts, especially in large regions in Romania or Eastern Europe, where bear populations frequently interact with human settlements mainly due to uncontrolled deforestation. Traditional methods often rely on reactive measures, intervening only after incidents occur. This paper proposes the concept of a proactive solution by using LoRa (Long Range) technology to create an efficient network with extremely low energy consumption to track bear movements in real time and realize an active monitoring area. The proposed system uses LoRa beacons attached to animals, providing long-distance and energy-efficient data transmission even in the difficult mountainous terrain of Romania, especially in the absence of GSM signal coverage. By analyzing signal parameters such as Received Signal Strength Indicator (RSSI) and Signal-to-Noise Ratio (SNR), we optimize the placement of a base station (gateway) to ensure maximum coverage and data reliability. In addition, a dynamic mapping system visualizes bear movements, allowing real-time monitoring and identification of potential human-wildlife conflict areas. The whole system also uses some notions and concepts specific to the Internet of Things and Machine Learning technologies, especially in the context of Industry 5.0. In addition to mapping, the system integrates a proximity alert mechanism that triggers preventive measures when bears approach human settlements. Unlike reactive strategies, this approach allows authorities to anticipate and mitigate risks, protecting both human lives and wildlife. The study highlights the importance of transitioning from traditional reactive models to proactive systems that prioritize prevention.**

Keywords — IoT, early warning system, environmental protection, real-time tracking, signal optimization, risk mitigation, bear

I. Introduction

Wildlife monitoring is an essential direction in the management of human-animal conflicts, especially in the vast regions of Romania and Eastern Europe, where interactions with bear populations have become increasingly frequent. These conflicts are amplified by the phenomenon of uncontrolled deforestation, which leads to the reduction of natural habitats and pushes wildlife towards areas inhabited by humans. In this context, traditional approaches, characterized by reactions after the occurrence of incidents, have proven insufficient both from the perspective of protecting human lives and conserving biodiversity.

This paper proposes an innovative solution based on LoRa (Long Range) technology, capable of implementing a proactive bear monitoring system. LoRa technology offers significant advantages in the efficient transmission of data over long distances, with low energy consumption, even in difficult mountainous terrain conditions, such as the Romanian Carpathians. While mobile networks can provide coverage near settlements and along main roads, their reliability in mountainous regions is often inconsistent due to dense forests, valleys and terrain obstacles. Even in areas with partial GSM coverage, connection loss is common, making real-time monitoring difficult. Deploying additional mobile network infrastructure in these remote areas is not only expensive but also technically challenging. Expanding GSM infrastructure in remote and mountainous areas requires substantial financial investments, including the installation of new base stations, power supply solutions, and extensive maintenance operations. In contrast, LoRa networks operate with minimal infrastructure, relying on energy-efficient gateways that cover vast areas with significantly lower costs. Additionally, LoRa devices can function autonomously for years due to their ultra-low power consumption, whereas GSM-based tracking solutions demand frequent battery replacements and higher operational expenses. These factors make LoRa a more viable, scalable, and cost-effective alternative for long-term wildlife monitoring.

LoRa technology offers a robust alternative, ensuring continuous wildlife monitoring through long-range, low-power communication, even in the absence of GSM coverage. Unlike conventional methods, the system uses LoRa devices attached to animals to collect and transmit data in real time, allowing for the monitoring of their movements in remote regions. This technological approach addresses the challenges of wildlife monitoring in remote areas and ensures the reliability of data transmission. By analyzing signal parameters such as Received Signal Strength Indicator (RSSI) and Signal-to-Noise Ratio (SNR), the work optimizes the location of base stations to ensure maximum coverage and superior data quality. In addition, a dynamic mapping system allows for real-time visualization of bear movements and identification of areas with a high risk of interaction with human populations.

This system integrates elements of the Internet of Things (IoT) and Machine Learning, highlighting its applicability in the context of Industry 5.0. Furthermore, proactive alerting mechanisms, based on the detection of bears approaching human settlements, allow the triggering of preventive measures, providing authorities with an effective tool for risk reduction. Thus, the transition is made from reactive models, which intervene only after incidents occur, to a preventive model, which prioritizes the protection of human lives and the conservation of wildlife. The paper emphasizes the importance of adopting such innovative and sustainable

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systems to harmonize the relationship between humans and nature.

II. Literature Review

In recent years, monitoring and conservation of large carnivore species have become key priorities in biodiversity management, especially in ecologically diverse regions such as Romania. Research [1] highlights how habitat characteristics, such as forest density, landscape fragmentation and altitude, influence populations of brown bears, wolves and lynxes. Mountainous regions with unfragmented forests are essential for the conservation of these species, while diversified land use can have a negative impact on carnivore populations. Spatial analysis models highlight the need to reduce habitat fragmentation and human expansion to maintain ecological connectivity.

Current bear monitoring systems in Romania are inefficient due to paper-based reporting methods and process fragmentation [2]. To improve data accuracy and prevention strategies, a centralized digital solution was proposed that would allow for precise location, real-time reporting and improved data access for authorities and researchers. A hybrid approach [3], combining track analysis and GPS telemetry, was used to estimate the density of brown bears in the Carpathians. The results showed a seasonal consistency in density, ranging from 11.3 to 14.7 individuals per 100 km², and the integration of genetic and GPS methods increased the accuracy of monitoring, providing a solid framework for long-term conservation planning.

Miniaturized radio transmitters play a key role in wildlife monitoring, with notable advances in power management and signal modulation technologies [4]. These devices, powered by batteries or energy harvesting systems, include omnidirectional antennas and integrated chip designs, ensuring the stability and reliability of data collection. Recent trends are aimed at integrating additional sensors for monitoring animal behavior, expanding the possibilities of application in the ecological field.

The impact of human activities [5] and forest degradation on the spatial behaviour of brown bears in Europe has been extensively studied [6]. GPS data collected from several bear populations indicate that human footprint and forest fragmentation significantly reduce the area of habitat use, causing bears to avoid areas with high anthropogenic influence. The results highlight the importance of maintaining and restoring natural habitats for the conservation of bear populations and the need to implement management strategies that minimize human impacts on them. Another study [6] analyzed the potential impact of the *A8* motorway on the bear population in the Eastern Carpathians. Using non-invasive methods, such as hair traps and genetic analysis, the researchers assessed bear distribution, genetic connectivity and the risks associated with habitat fragmentation. The study demonstrated the existence of genetic connectivity between individuals located on both sides of the proposed route, which highlights the importance of maintaining functional ecological corridors. The more frequent presence of bears near human settlements suggests a certain tolerance towards human presence, but this proximity may increase the risks of conflict. To limit the impact of highway construction on the bear population, the study [7] recommends the implementation of wildlife crossing structures and measures to control poaching and the impact of stray dogs.

Research on LoRa technology in sensor networks has demonstrated that it is an efficient solution for long-distance data transmission with low power consumption [8]. A notable study developed a LoRa-based geolocation system for sensor networks, optimizing communications over large areas where other technologies would be ineffective or too expensive [8], [9], [10]. Experimental results showed that the proposed system provides satisfactory accuracy in sensor location and provides reliable communication over considerable distances, making LoRa technology ideal for applications in precision agriculture, environmental monitoring, and smart infrastructures. The use of LoRa technology in wildlife monitoring has also been analyzed in forest environments [11]. A study conducted in Italy evaluated the performance of LoRa communications depending on vegetation density, demonstrating that signal coverage varies significantly. In dense forests, the maximum LoRa range was approximately 860 meters, while in areas with less vegetation, the coverage reached up to 2050 meters. It was also found that the 433 MHz band provides better coverage compared to the 868 MHz band, due to lower signal attenuation in dense forest environments. These findings highlight the importance of selecting optimal communication parameters for wildlife monitoring applications and smart agriculture. Overall, these studies highlight the need for reliable and low-power solutions for remote wildlife monitoring, and LoRa technology has been shown to be the most effective in various environmental conditions.

III. Materials and Methods

To implement a monitoring system based on LoRa technology, the adopted methodology focused on the design, simulation and analysis of a system capable of operating in varied terrain conditions and meeting the needs of a mountainous environment with limited GSM coverage. This technical and integrative approach aimed at achieving a real-time wildlife monitoring system with minimal energy consumption (see Fig. 1).

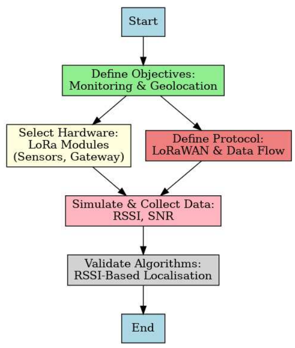

Fig. 1. Flowchart for proposed LoRa-based monitoring system.

The proposed system consists of a distributed architecture, composed of hardware modules, a communication infrastructure and software algorithms that optimize data collection and processing [13], [14]. LoRa modules were selected due to their long-distance transmission characteristics and low energy consumption. The analysis focused on the signal propagation characteristics in difficult conditions and on the validation of the algorithms developed for localization based on RSSI (Received Signal Strength Indicator).

The system architecture consists of three main components:

LoRa end nodes: These are equipped with sensors for data collection (e.g., presence of fauna, temperature, humidity). The nodes were configured to use the LoRa module for energy-efficient transmissions. Each node was equipped with LoRa modules, operating at 868 MHz, these modules provide long-range data transmission with minimal power consumption, making them ideal for remote monitoring applications, lithium-ion batteries with low discharge rates, ensuring prolonged operational lifespans and microcontroller - integrated with system-on-chip (SoC) solutions to manage data acquisition, preprocessing, and transmission tasks.

Gateways: These devices function as data collection points, relaying the information to the central server. The placement of the gateways was done based on simulations of RSSI and SNR parameters to ensure optimal coverage.

Central Server: The central server manages the received data, applies geolocation algorithms and provides the information in an easy-to-use visual interface.

To test and validate the network, experiments were conducted in three distinct scenarios: dense mountainous terrain, open spaces and urban environments. Each scenario allowed the evaluation of the network performance in terms of interference, transmission distance and localization accuracy. The obtained dataset includes over 25,000 measurements that captured essential parameters such as RSSI, SNR and data transmission rate. To determine the position of the end nodes, trilateration methods were used, which calculate the distance between nodes and gateways based on RSSI values. More precisely a relationship between the received power (RSSI) and the distance can be obtained. Its value, simplified here for the reference distance of 1 m, is usually expressed as (1):

$$RSSI = -(10 \cdot n \cdot \log_{10} d - A) \quad (1)$$

where A is the received power in dBm when the distance between the transmitter and receiver antenna is 1 m and n is the loss parameter (or loss exponent) of the specific medium. The distance d is obtained as (2)[12]:

$$d = 10^{\left(\frac{A-RSSI}{10*n}\right)} \quad (2)$$

In addition, advanced machine learning algorithms, such as Multi-Layer Perceptron neural networks, were applied to reduce prediction errors [13]. Experimental data were used to calibrate the mathematical models and train the neural networks, thus obtaining more accurate results. The evaluations demonstrated that the designed network provides coverage of up to 2.5 km in open spaces and between 800 and 1000 meters in densely vegetated terrain. The energy consumption of the end nodes allows for long-term operation, and the geolocation accuracy recorded an average error of 7-10%. The tests also highlighted the need for additional strategies to reduce interference in complex urban environments. The proposed methodology led to the realization of a scalable and robust monitoring system, usable for the prevention of human-wildlife conflicts. The system demonstrates the viability of LoRa technology as a solution for real-time monitoring applications in remote regions, having a positive impact on environmental protection and on the optimization of human-wildlife interaction.

Using all the values from a file related to LoRa nodes, a complete and cleaned dataset was built, which was then used later in training a neural network model and simulating the smart grid. In the first stage, the data was processed by standardizing the columns, having the structure: Node (node identifier), RSSI (Received Signal Strength Indicator), SNR (Signal-to-Noise Ratio) and Position (node position). The values were converted to numeric type, eliminating incomplete or invalid rows to ensure the consistency of the dataset. The cleaned dataset was used to train an artificial neural network (MLPRegressor) with three hidden layers, having sizes of 50, 30 and 10 neurons. The dataset was split into 80% training and 20% test data, ensuring a balanced distribution for performance evaluation. This split was chosen to provide enough data for learning while maintaining a representative test set for validation. The RSSI and SNR values served as input variables, and the position of the nodes was the target variable. The model was evaluated using the mean square error (MSE) and R2 score, revealing a moderate performance, with room for improvement by optimizing the hyperparameters and network structure. In parallel, the simulation of the smart network involved generating random positions for nodes and gateways in a two-dimensional space. Connectivity was evaluated based on the Euclidean distance between nodes and gateways, considering a coverage radius of 30 units. The network coverage rate was determined as the percentage of connected nodes, and the analysis indicated a total coverage of 49.79%. The results suggest the need to optimize the placement of gateways to improve network coverage, a critical aspect for applications in rugged or isolated terrain.

The analysis and simulation results highlight the performance of the LoRa network in a prediction and connectivity system. The neural network used to estimate node positions based on RSSI and SNR values obtained an R^2 score of 0.0587, indicating a limited ability to model position variability. This result, associated with a mean square error (MSE) of 422.25, reflects the difficulties encountered in predicting positions based on these parameters alone, suggesting the need for additional features or model optimizations.

Simulating network connectivity in a two-dimensional space, with 3 randomly placed gateways and a coverage radius of 30 units, indicated a coverage rate of 49.79% (see Fig. 2). Almost half of the nodes were connected to at least one gateway, and the generated map clearly highlights the covered areas (connected nodes, represented in red) and uncovered areas (isolated nodes, represented in blue), while gateways are marked with green symbols.

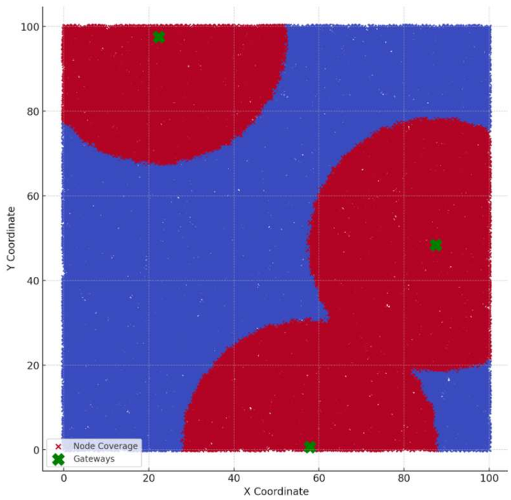

Fig. 2. Simulated network coverage with full dataset.

The results highlight the challenges of accurate prediction and ensuring efficient coverage in complex environments. The moderate performance of the neural network and the low coverage rate suggest the need to optimize the placement of gateways or expand the network with additional units. These conclusions provide a basis for future adjustments and to improve the implementation of the system in practical applications.

An advanced simulation integrating machine learning using TensorFlow was also implemented to analyze and optimize the connectivity of LoRa networks based on synthetic parameters such as RSSI and SNR. The model uses a trained artificial neural network to predict the connectivity of nodes relative to gateways strategically placed in a two-dimensional space. The simulation provides a clear representation of the distribution of connected and unconnected nodes, based on artificially generated input data.

Fig. 3 showing the performance during training highlights a progressive increase in the accuracy of the model over 50 epochs. Both the training and validation data demonstrate a convergence towards high accuracy values, with a final performance of approximately 97%. This indicates a good generalization of the model and a high ability to differentiate between connected and unconnected nodes.

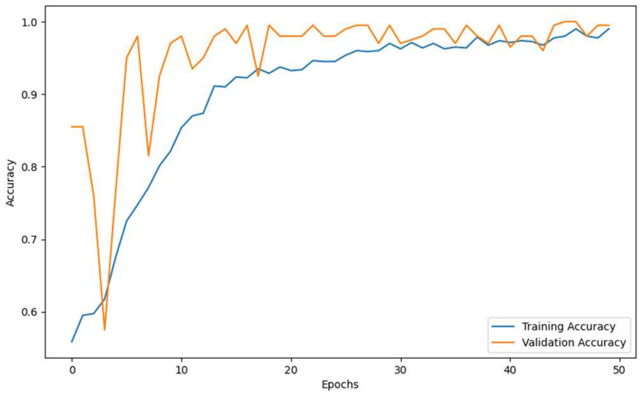

Fig. 3. Model training performance.

The generated coverage map provides a detailed visualization of the spatial distribution of LoRa nodes and their connectivity status relative to strategically placed gateways (see Fig. 4). Red dots represent nodes successfully connected within the designated coverage area, while blue dots indicate unconnected nodes that fall outside the effective communication range. Green "X" markers signify the locations of gateways, positioned using a K-Means clustering algorithm to optimize network efficiency and maximize coverage distribution. While the network ensures significant connectivity in the proximity of gateways, certain areas remain uncovered, highlighting limitations in the current configuration. These gaps may be caused by signal attenuation, interference, or an insufficient number of gateways, requiring further adjustments to enhance network performance. Increasing gateway density in critical regions, optimizing transmission power to extend communication range, or repositioning nodes for better proximity could help improve connectivity. Another approach could involve integrating a mesh network mechanism, allowing certain nodes to act as relays and bridge communication gaps. Despite these limitations, the network effectively covers a substantial portion of the deployment area, ensuring energy-efficient and cost-effective communication. However, the presence of unconnected nodes suggests the need for refinements to achieve seamless real-time monitoring, particularly for large-scale applications such as wildlife tracking, environmental surveillance, and industrial IoT systems. Improving gateway placement strategies and leveraging advanced network optimization techniques would allow for more comprehensive coverage, ensuring a robust and reliable long-range communication system tailored to the specific needs of the monitored region.

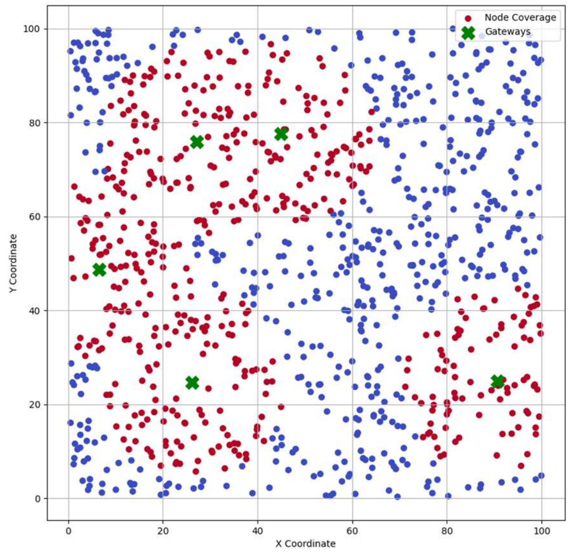

Fig. 4. Advanced network coverage simulation.

The simulation highlights the potential of the application in optimizing LoRa networks for monitoring applications, clearly showing both the current limitations of gateway placement and the possibilities for improvement. The results obtained demonstrate the applicability of the proposed method and provide a solid basis for further integration of real data for validation and expansion. A new simulation was conducted to predict bear movements using a Long Short-Term Memory (LSTM) model, which is specifically designed to learn temporal sequences and complex relationships between data. We generated synthetic data for bear trajectories as points (x, y) over 100 time steps, representing a two-dimensional random movement. To improve predictions, we added additional features, such as speed and direction of movement, which provide additional contextual information for the LSTM model. The model was trained for 100 epochs, using a dataset constructed from 10-step temporal sequences, which served as input for predicting the next step (x, y) (see Fig. 5).

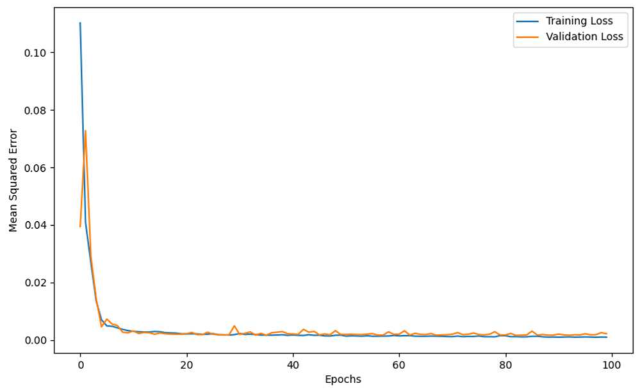

Fig. 5. Model training performance (LSTM).

The loss function used was the mean square error (MSE), which allowed us to evaluate the difference between the predicted and actual values. The training and validation losses decrease significantly over the epochs, reaching almost constant values after about 30 epochs. This indicates that the model trained efficiently, avoiding both under- and over-fitting. The low loss suggests that the model learned the synthetic movement patterns well.

The predicted trajectory, represented by a dotted line, follows a general direction consistent with the bear's movement, but there is significant deviation from the original trajectory in some regions. This indicates that the model learns the general trends of the movements, but may not be accurate enough to capture fine details (see Fig. 6).

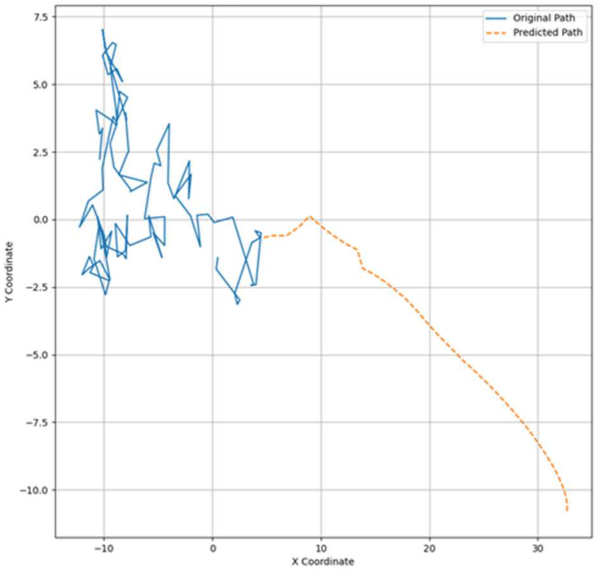

Fig. 6. The predicted trajectory simulation.

Incorporating external factors, such as physical barriers (mountainous terrain, rivers) or points of interest (food resources, preferred habitats), could improve the accuracy of the predictions. A larger and more diverse dataset would allow the model to learn the movement patterns better. Extending the model architecture with more layers or using hybrid neural networks that combine LSTM with dense layers could increase performance. The simulation highlights the ability of the LSTM model to predict general movement trends, but also highlights the challenges of capturing the complex details of trajectories. This represents an important step in developing an AI-based predictive system for proactively managing human-wildlife conflicts.

Finally, we integrated an alerting module into the simulation that detects the proximity of bears to populated areas, using the predictions of the LSTM model. Populated areas were defined as fixed points on the map, and a radial distance criterion was used to determine whether a predicted bear was in a risk area. This module was implemented to signal critical locations in real time, marking alert points on the predicted bear path.

The output shows the original and predicted trajectories of a bear, along with the locations of populated areas represented by red circles (see Fig. 7). In addition, alert points, where the distance between the bear predictions and a populated area fell below the established critical radius, are highlighted by orange markers. The resulting graphs demonstrate that the system can correctly identify risk points, such as when a bear is dangerously close to a populated area. These points are clearly visualized on the predicted path, providing a clear indication of when and where authorities' intervention might be required.

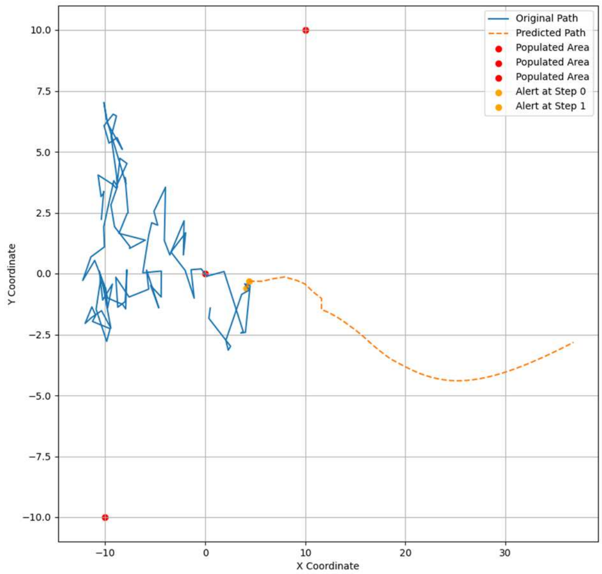

Fig. 7. Bear movement prediction with alerts.

This functionality considerably improves the practical utility of the system, providing an anticipatory mechanism for managing human-wildlife conflicts. Real-time alerting allows for preventive measures to be taken before an incident occurs, thus supporting proactive conservation and public safety strategies. The model simulates a realistic scenario of how such a system might work in practice, using synthetically generated data and artificial intelligence predictions to address a critical ecological and social problem.

The comparative radar chart (see Fig. 8) illustrates the distinct advantages of LoRa technology over traditional GSM-based systems across key performance metrics. LoRa excels in coverage efficiency, scalability, and network reliability, making it a superior choice for remote and large-scale deployments. Its ability to maintain long-range connectivity with minimal infrastructure enables it to outperform GSM in challenging terrains where signal loss and fragmentation typically occur.

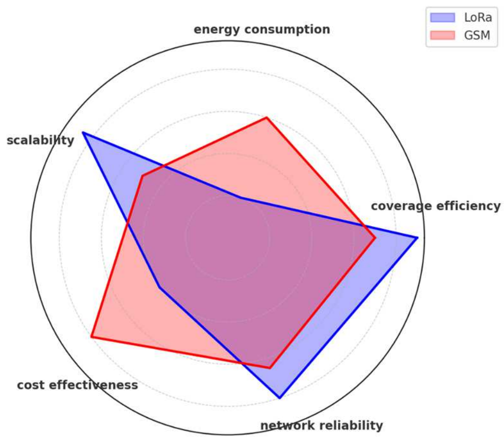

Fig. 8. Optimizing long-range connectivity: a comparative analysis of LoRa and GSM for efficient network deployment.

Despite these advantages, power consumption remains an area where GSM has an advantage, as LoRa uses low-power transmissions, sacrificing data speed for energy efficiency. Also, from a cost perspective, GSM networks are already integrated into existing infrastructure, requiring lower initial investments, making them more suitable for urban applications. However, LoRa's ability to operate autonomously in large environments, without the need for costly infrastructure expansion, compensates for these limitations and makes it a viable solution for long-term monitoring in remote environments. This paper highlights the potential of LoRa technology in environmental monitoring and wildlife tracking, demonstrating its efficiency in long-distance communication with low energy consumption. Although current studies have not confirmed absolute efficiency, the advantages of LoRa in remote areas justify its application in proactive conservation strategies.

We propose a LoRa-based system for monitoring the brown bear population, with the aim of preventing human-wildlife conflicts [15]. Each bear would be equipped with a LoRa device, ensuring continuous tracking, even in rugged terrain or in areas without GSM signal. By integrating artificial intelligence algorithms, the system anticipates bear movements, allowing authorities to intervene preventively, before conflicts arise.

This proactive approach improves the coexistence between humans and wildlife, preventing drastic measures such as relocation or elimination of animals [17]. The integration of IoT and AI technologies offers a scalable solution, adaptable to other regions with high biodiversity [16]. This system exemplifies how technology can transform wildlife conservation, moving from reaction to prevention, providing sustainable and intelligent management of human-wildlife interactions in the modern era [18], [19].

Conclusions

This paper presents a proactive wildlife monitoring system using LoRa technology and artificial intelligence to prevent human-bear conflicts. Unlike traditional reactive methods, the proposed approach anticipates risks and enables preventive interventions, protecting both human communities and wildlife. The use of LoRa beacons, whether as collars or subcutaneous implants, ensures real-time tracking even in rough terrain or in the absence of GSM signal. AI-based predictive models process the collected data, allowing authorities to detect potential threats early and respond accordingly. Simulations confirmed the system's ability to optimize connectivity and gateway placement, improving coverage efficiency. AI integration enhanced location accuracy and movement prediction, but challenges remain, such as the need for higher network density or extended coverage range. Despite these limitations, the system offers a scalable and sustainable solution for mitigating human-wildlife conflicts, with potential applications in other biodiversity-rich regions.

By combining IoT and AI technologies, this approach highlights the role of smart solutions in environmental protection and wildlife conservation. Ultimately, this system fosters a harmonious coexistence between humans and nature, promoting innovative strategies to address the ecological challenges of the 21st century.

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