Comparative Study of EVOA for Optimising Resource Allocation in LoRaWAN

Alen Scaria

Department of Computer Science and Engineering
National Institute of Technology Rourkela

Abstract

In Low-Power Wide Area Networks (LPWANs), LoRa (Long Range) technology has emerged as a promising wireless communication solution, utilising Chirp Spread Spectrum (CSS) modulation to achieve robust, long-range data transmission. Building upon LoRa, the **LoRaWAN** protocol manages device transmission timing and message formatting, making it particularly suitable for Internet of Things (IoT) deployments across smart cities and agricultural applications. Despite its advantages, resource allocation in LoRaWAN networks has significant optimization challenges, particularly in balancing bandwidth utilisation, power consumption, and transmission timing. Current approaches struggle to maintain reliable data transmission over extended distances while adhering to low-power constraints. This work presents a novel application of the **Energy Valley Optimization Algorithm (EVOA)**, a physics-inspired metaheuristic technique, to address these challenges. The proposed EVOA-based system aims to optimise resource allocation by simultaneously minimising energy consumption and signal interference while maximising network throughput. Future work will involve comparing EVOA's performance with other metaheuristic techniques in LoRaWAN.

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Chapter 1

Introduction

The Internet of Things (IoT) has become a transformative technology, connecting billions of devices and enabling seamless communication across a wide range of applications, from smart cities to industrial automation and agriculture. In IoT networks, end devices typically operate on limited power sources like batteries, making efficient energy management critical for sustaining network operations over extended periods.[1] Furthermore, the rapid expansion of IoT deployments has led to dense networks of connected sensors and actuators, creating a growing demand for scalable, energy-efficient communication technologies that can support a high volume of devices without sacrificing performance. [2]

Among these, Low Power Wide Area Networks (LPWAN) stand out as a suitable choice for IoT networks, with features like low power consumption, cost-effective deployment, and long-range communication. Within LPWAN, LoRaWAN (Long Range Wide Area Network) is particularly prominent due to its suitability for long-range, low-power communication over unlicensed bands, making it ideal for large-scale IoT deployments. [3]

However, achieving optimal resource allocation in LoRaWAN is challenging because it requires balancing low power usage with reliable data transmission across extended distances. Effective resource allocation, optimizing parameters like transmission power, bandwidth, and data rate, is essential to meet the diverse demands of IoT applications while addressing constraints like interference and duty cycle limitations.

1.1 Problem Definition

Despite its advantages, LoRaWAN's current resource allocation methods struggle with scalability and adaptability in dynamic IoT environments. The problem entails developing a more adaptive and energy-efficient resource allocation approach for LoRaWAN that can dynamically respond to fluctuating network conditions. This challenge involves optimizing key network parameters to reduce interference and manage power consumption sustainably.

1.2 Objectives

The primary objective of this research is to evaluate the Energy Valley Optimization Algorithm (EVOA) as a solution for efficient resource allocation in LoRaWAN networks, focusing on enhancing network performance metrics such as scalability, energy efficiency, and data reliability. To achieve this:

- Implement EVOA in a simulated LoRaWAN environment
- Configuring it to optimise key network parameters.
- Compare EVOA with other prominent metaheuristic algorithms like, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE)—to evaluate its relative performance.
- Evaluate the performance among these algorithms.

Chapter 2

Project Work

This section provides an overview of the current progress in understanding the topic, along with the proposed approach for addressing the problem.

2.1 Literature Review

Several studies have explored diverse research approaches to enhance resource allocation in LoRaWAN networks, focusing on optimising transmission power, energy efficiency, and network performance.

In 2020, a study done by Park et al.[4] developed a resource allocation system using reinforcement learning techniques for LoRaWAN. Their system reduced transmission energy by dynamically adjusting transmission power based on identified attributes, optimising network parameters like spreading factor, channel, and transmission power with deep reinforcement learning. Experimental results indicated that the system achieved superior throughput performance, enhancing overall network efficiency.

Gava et al.[5] proposed an efficient resource distribution system in 2023 for LoRaWAN using a minimum-cost spanning tree algorithm. This approach minimised computational costs and energy utilisation in resource allocation by combining a minimum-cost spanning tree with a Variable Neighborhood Search (VNS) algorithm. Additionally, the VNS helped locate repeaters within the network, significantly lowering time-on-air and energy consumption by optimising attributes like transmission power and spreading factor (SF).

In another 2020 study, Liao et al.[6] introduced a model-driven, deep reinforcement learning-based resource distribution system. They developed a Deep Neural Network (DNN)-based optimization network incorporating Alternating Direction Method of Multipliers (ADMM) iterative techniques to improve spectral efficiency, energy efficiency, and fairness. Their Channel Information Absent Q-learning (CIAQ) algorithm minimised training data requirements and optimised spectral efficiency, achieving faster convergence speeds compared to traditional methods.

Zhang et al.[7] presented a two-stage virtual network embedding algorithm, TS-DRL-VNE, in 2020. This deep reinforcement learning-based algorithm addressed limitations in Virtual Network Embedding (VNE) by introducing a Full Attribute Matrix (FAM-DRL-VNE) and Matrix Perturbation Theory (MPT-DRL-VNE) to enhance resource allocation in substrate networks. The proposed model demonstrated significant improvements over existing VNE algorithms in terms of resource management and embedding efficiency.

Zhao et al.[8] utilised reinforcement learning techniques in 2019 to ensure quality of service in cellular networks. Their multi-agent reinforcement learning approach employed a Dueling Double Deep Q-Network (D3QN) protocol to optimise resource allocation by considering factors like reward function, state, and action. This approach outperformed traditional methods in computational efficiency and improved service quality within the cellular network.

In 2023, Jouhari et al.[9] developed a deep reinforcement learning system aimed at maximising energy efficiency in LoRa networks. The system utilised flying gateways (GW) and LoRa end devices, improving network lifetime by optimising SF allocation and wireless link management. The results showed that the system achieved higher energy efficiency and outperformed existing techniques.

Finally, Minhaj et al.[10] proposed a combination of centralised and decentralised learning techniques in 2023 to allocate resources in LoRaWAN. By addressing SF allocation and transmission energy optimization, this hybrid approach resolved issues related to contextual bandit problems in devices and supervised learning challenges in transmission energy control. Their model showed enhanced performance in resource management when compared to other contemporary methods.

2.2 Proposed Algorithm: Energy Valley Optimization Algorithm (EVOA)

The Energy Valley Optimization Algorithm (EVOA) is a physics-inspired metaheuristic optimization technique designed to solve complex, high-dimensional problems. Inspired by the behaviour of subatomic particles, EVOA models candidate solutions as particles in an energy state, where each particle represents a potential solution. In the context of LoRaWAN resource allocation, a candidate solution is typically a combination of optimised parameters such as spreading factor, transmission power, and channel allocation, for each device in the network. These parameters collectively represent an optimised configuration that balances network energy efficiency, interference management, and data throughput.

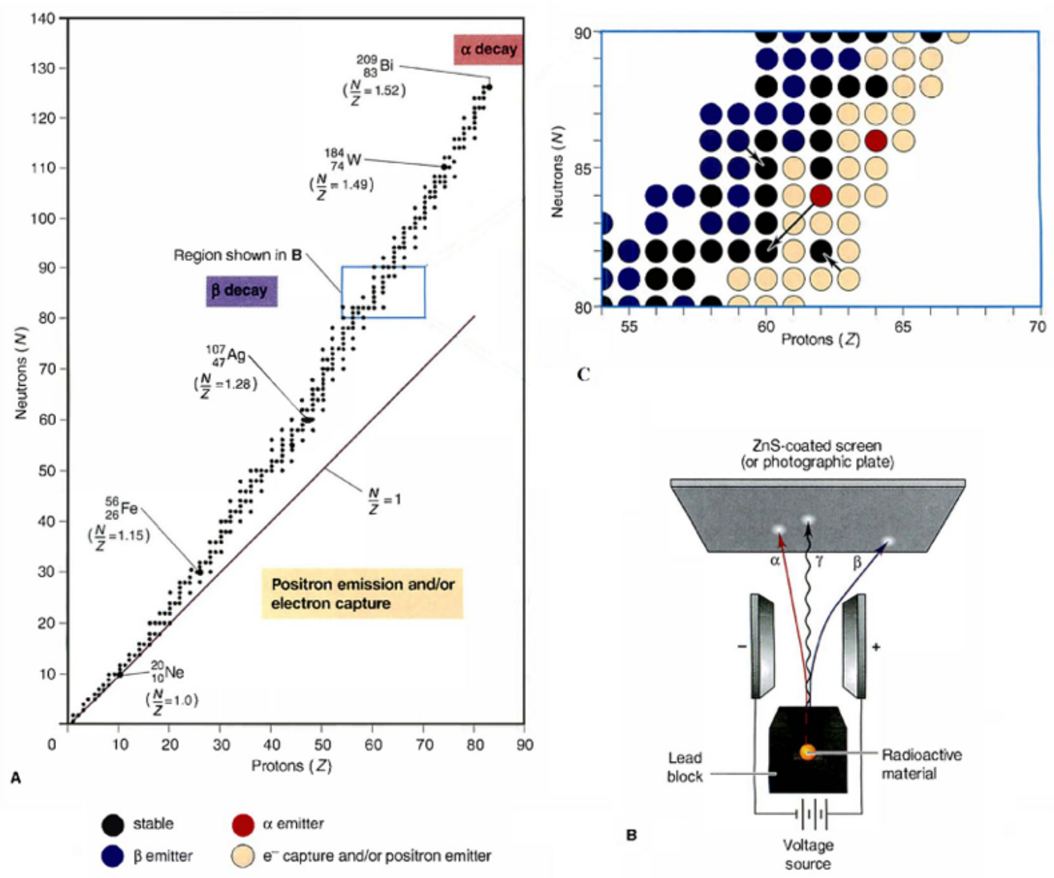

Figure 2.1: (A) Stability band for particles (B) Process of emission (C) Different types of decay

EVOA draws on the principles of particle stability, mimicking how unstable particles emit energy over time to achieve stability. In this analogy, particles adjust their positions in the search space, seeking lower energy states that correspond to better optimization outcomes.[11] Each particle in EVOA is assigned an initial stability, which is incrementally adjusted as particles explore the search space. Particles decay toward more stable configurations, emulating a natural process of evolution toward optimal solutions.

2.2.1 Steps of the Energy Valley Optimization Algorithm (EVOA)

The pseudocode of the EVO algorithm is indicated in Algorithm 1.[12] The steps involved are as follows:

- **Initialization:** The algorithm begins by initialising a population of particles (candidate solutions) randomly within the defined search space. Each particle's position represents a specific combination of transmission parameters.

- **Fitness Evaluation:** Each particle is evaluated based on a fitness function that assesses how well it meets the optimization criteria, such as minimising energy consumption while maximising throughput. This fitness function can be influenced by factors like Signal-to-Interference-plus-Noise Ratio (SINR) and overall network performance.

- **Particle Movement:** Inspired by the decay processes in physics, particles adjust their positions in the search space based on their stability levels. Particles with lower energy states (less optimal solutions) will decay or move towards more stable configurations. This movement mimics the natural tendency of particles to seek stability, where they adjust their parameters based on feedback from their environment.

- **Iteration and Convergence:** The process continues iteratively, with particles adjusting their positions based on individual performance and collective knowledge from neighbouring particles. Over time, this leads to convergence towards optimal solutions that balance energy efficiency and communication effectiveness.

- **Final Selection:** After several iterations, the best-performing particle(s) are selected as the optimal solution(s) for resource allocation in LPWAN.

```
Find the location of all candidate solutions present in the
search space.
Determine the fitness of the solution candidates in terms
of OFMa.
while count of function evaluation < function evaluation
do
    Find the enrichment bound FC of all particles.
    Find the particle based on the best stability bound.
    for j = 1 to o do
        Determine the stability bound of the particle.
        Find the neutron enrichment level of the particle
        OFMa.
        if OFM < FC then
            Find the stability bound of the particle.
        end if
        if TMa > TC then
            Find index alpha I and index alpha II.
        end if
    end for
end while
Achieve best solution.
```

Figure 2.2: Algorithm.1

2.3 Comparison with Other Algorithms

Various optimization algorithms have been employed for resource allocation in LPWAN, each with strengths and limitations in balancing efficiency, energy use, and computational complexity. In this study, we aim at comparing the results of the EVOA algorithm with some of the traditional optimisation algorithms namely- Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE).

2.3.1 Genetic Algorithms (GA)

- Genetic Algorithms have been widely applied in network optimization due to their robust search capabilities and adaptability. They operate by simulating evolutionary processes, including selection, crossover, and mutation, to evolve solutions over generations.

- While effective, GAs may struggle with convergence speed in high-dimensional problems, often requiring significant computational resources. In LPWAN contexts, GAs have shown improvement in network throughput.

2.3.2 Particle Swarm Optimization (PSO)

- PSO is a bio-inspired algorithm based on the social behaviour of particles. It has been successfully applied in LPWAN optimization to reduce energy consumption and manage interference.

- However, PSO can suffer from premature convergence and is prone to getting trapped in local optima, particularly in dynamic network conditions.

2.3.3 Differential Evolution (DE)

- Differential Evolution is another popular metaheuristic algorithm that performs well in continuous optimization problems. DE's ability to efficiently explore search spaces makes it suitable for LPWAN resource allocation, where multiple conflicting objectives exist.

- DE, however, can be computationally intensive, especially when optimising in high-dimensional spaces. EVOA, with its energy valley-inspired approach, often requires fewer evaluations to reach optimal solutions.

Chapter 3

Conclusion

3.1 Future Work

By reviewing existing approaches and understanding the foundational principles of EVOA and other metaheuristic algorithms, we see EVOA as a promising method for enhancing network performance. As part of the future work, the next steps will be implementing the EVOA algorithm in a LoRaWAN setup to evaluate its effectiveness in real-world scenarios. After which we will conduct a comparative analysis with other established metaheuristic algorithms, like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE), as mentioned earlier.

3.2 Conclusion

In conclusion, this report has examined the potential of the Energy Valley Optimization Algorithm (EVOA) for optimising resource allocation in LoRaWAN networks, which is considered essential for supporting scalable, energy-efficient IoT applications. By analysing LoRaWAN's requirements and the limitations of traditional resource allocation methods, this study identified EVOA as a promising solution to explore complex optimization problems.

Overall, this study demonstrates the potential impact of advanced optimization techniques like EVOA in IoT networks, setting the stage for a deeper exploration of metaheuristic methods in LoRaWAN resource management. This work paves the way toward more efficient, reliable, and scalable networks that can meet the growing demands of the IoT ecosystem.

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