Comparative Study of EVOA for Optimising Resource Allocation in LoRaWAN

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Comparative Study of EVOA for Optimising Resource Allocation in LoRaWAN

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November 11, 2024

Supervisor's Certificate

This is to certify that the work presented in the project report entitled *Comparative Study of EVOA for Optimising Resource Allocation in LoRaWAN* submitted by *Alen Scaria*, Roll Number 121CS0237, is a record of original research carried out by him under my supervision and guidance in partial fulfillment of the requirements of the degree of *Bachelor of Technology* in *Computer Science and Engineering*. Neither this project report nor any part of it has been submitted earlier for any degree or diploma to any institute or university in India or abroad.

Judhistir Mahapatro

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. However, due to the densification of IoT devices, LoRaWAN technology presents new challenges, especially in dense networks where resource allocation struggles to balance bandwidth utilization, 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 comparative study of the **Energy Valley Optimization Algorithm (EVOA)**, a physics-inspired metaheuristic technique, and other heuristic algorithms, such as Genetic Algorithm, Particle Swarm Optimisation Algorithm, and Differential Evolution, for optimizing resource allocation in LoRaWAN. The study aims to evaluate the performance of these algorithms in addressing challenges such as energy consumption, signal interference, and network latency in dense IoT networks. Future work will focus on developing an efficient resource allocation method using EVOA as the optimization algorithm to achieve optimal performance in LoRaWAN networks.

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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, particularly in dense networks with high device concentration and signal interference. The challenge is developing a more adaptive and energy-efficient resource allocation approach that can dynamically respond to fluctuating network conditions while optimizing key 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.

In 2023, Jouhari et al.[7] 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.[8] 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.

The base paper introduces a novel approach to resource allocation in Low Power Wide Area Networks (LPWANs) using a hybrid optimization algorithm, HC-EVOA, integrated with reinforcement learning techniques. The study focuses on optimizing key parameters such as channel, spreading factor, and transmission power to enhance throughput and reduce energy consumption.[9]

2.2 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.

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.[10] 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.

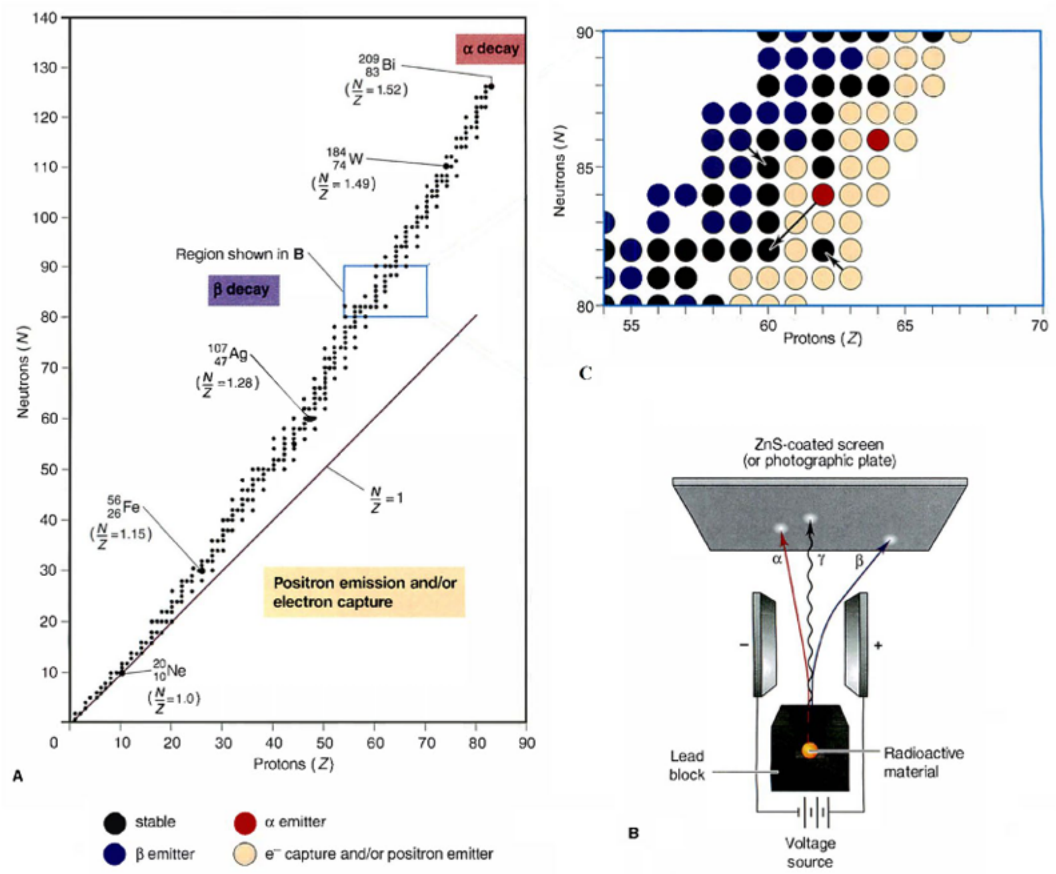

Figure 2.1: (A) Stability band for particles (B) Process of emission (C) Different types of decay

2.2.1 Steps of the Energy Valley Optimization Algorithm (EVOA)

The steps involved in the algorithm 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.

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) and Particle Swarm Optimization (PSO).

2.3.1 Genetic Algorithms (GA)

- Genetic Algorithms have been widely applied in network optimization due to their robust search capabilities and adaptability.[11] 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)

- Particle Swarm Optimization (PSO) is a bio-inspired metaheuristic algorithm that mimics the social behavior of particles, such as birds flocking or fish schooling, to solve optimization problems.
- In the context of Low Power Wide Area Networks (LPWANs), including LoRaWAN, PSO has been effectively used to optimize key parameters such as spreading factor, transmission power, and channel allocation to minimize energy consumption and reduce interference.[12]
- While PSO can effectively optimize parameters for improving energy efficiency and reducing interference, it can face challenges such as premature convergence and getting trapped in local optima, especially in dynamic and densely populated IoT networks.

2.4 Methodology

This section describes the methodology and progress made in this research, focusing on the design, implementation, and evaluation of the Energy Valley Optimization Algorithm (EVOA) for resource allocation in LoRaWAN networks. The study incorporates a LoRaWAN simulation environment where EVOA was applied to optimize key parameters. Comparative analysis with traditional algorithms, including Genetic Algorithm (GA), and Particle Swarm Optimization (PSO), was conducted to evaluate EVOA's performance.

2.4.1 LoRaWAN Setup

The LoRaWAN setup for this project was implemented using a Python-based simulation framework (SimPy) to model the essential components of a LoRaWAN network, including devices, gateways, and performance metrics. The simulation environment randomly distributed a specified number of devices and gateways within a defined area, with each device initialized with parameters such as spreading factor, bandwidth, and transmission power. Devices were assigned to the nearest gateway to ensure efficient communication. Key metrics, including packets sent and received, energy consumption, latency, packet delivery ratio (PDR), and energy efficiency, were recorded.

2.4.2 Implementation of EVOA

- The Energy Valley Optimization Algorithm (EVOA) was implemented using the Mealpy optimization library, a comprehensive Python package for metaheuristic algorithms. The implementation leverages the Mealpy library's EVO module on optimizing key parameters for a LoRaWAN network like Spreading Factor(SF), Transmission Power(TP) and Channels.

- The fitness function was carefully designed to capture multiple performance metrics by strategically balancing key network performance indicators. The function aims to maximize packet delivery ratio (PDR), minimize network latency, and maximize energy efficiency simultaneously.

$$\text{Fitness} = \text{PDR} - \frac{\text{Latency}}{10} - \frac{1}{\text{Energy Efficiency}} \tag{2.1}$$

- The simulation was run for different list of number of nodes and gateways and the results for PDR, latency and energy efficiency was obtained.

2.4.3 Implementation of Other Algorithms

- Particle Swarm Optimization (PSO) was ran on the LoRaWAN setup to optimize the device parameters like spreading factor, bandwidth, and transmission power. The algorithm initializes a population of particles. Particles move within the search space, updating their positions based on their own best-known position on the basis of fitness score defined and the global best position identified so far. This process continues until the best possible settings are found.

- Genetic Algorithm (GA) is used to optimize LoRaWAN network parameters by simulating natural selection. A population of potential solutions, each representing a different set of parameters like transmission power, spreading factor, and bandwidth, is created. These solutions are evaluated based on their fitness, which measures factors like energy efficiency and network throughput. The fittest solutions are selected to reproduce, creating new generations of solutions through crossover and mutation. This iterative process allows GA to evolve towards optimal configurations that balance energy consumption and network performance.

2.4.4 Comparison of the Results

- The results for key performance metrics, including Packet Delivery Ratio (PDR), Energy Efficiency, and Latency across various LoRaWAN configurations, were computed for each algorithm and stored in dedicated variables.

- These results were then consolidated into a CSV file. Comparative plots for each metric across different nodes was plotted using Python's Matplotlib library, facilitating a comprehensive analysis of algorithmic performance.

2.5 Findings

The comparitive analysis between the results obtained for each algorithm on the LoRaWAN setup showed some insight into the performance of these algorithms. EVO algorithm seems to show slightly better results in overall case for each metric calculations like higher PDR, good overall Energy Efficiency and lower Latency results for denser environment.

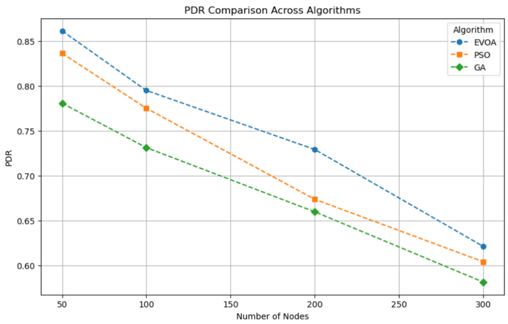

Figure 2.2: PDR

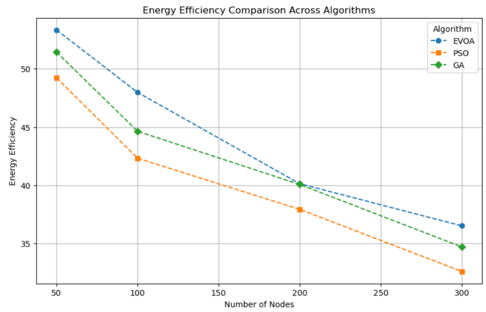

Figure 2.3: Energy Efficiency

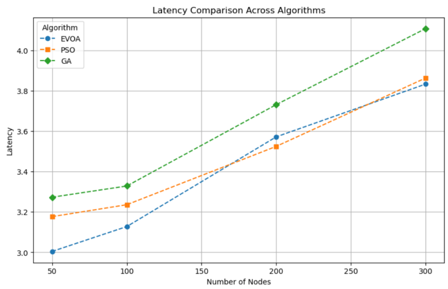

Figure 2.4: Latency

Figure 2.5: Metrics Comparison

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, there's a scope of integration of Machine Learning techniques to learn the information of the nodes and imporve resource allocation based on this knowledge and EVO optimization algorithm.

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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