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# Overall Power Optimization of Thread Mesh Wireless Networks


by

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ABSTRACT

This research investigates power optimization in Thread mesh wireless networks by conducting a series of experiments aimed at reducing overall power consumption while maintaining reliable network performance. Transmission power serves as a key parameter for achieving energy efficiency, and the study focuses on two algorithmic approaches: the Monte Carlo Method (MCM) and the Genetic Algorithm (GA). The research involves determining the optimal network configuration and transmission power constraints, selecting appropriate hardware, building the network, and developing the algorithms. Data is collected and analyzed from various network modes and devices across two locations, including lab and home environments, to ensure diverse and representative results. MCM emphasizes optimal network configuration alongside initial transmission power, while GA targets optimal transmission power settings. The findings indicate that both MCM and GA outperform the Maximum method in power optimization, with GA offering the best results. By effectively minimizing energy usage, GA ensures network performance is not compromised. The research emphasizes the importance of sustainability by promoting energy-efficient solutions that minimize environmental impact. The project's focus on energy efficiency and reduced power consumption makes it environmentally friendly and sustainable, contributing to reduced energy waste and lowering the carbon footprint associated with IoT networks. Additionally, the research process involves the application and development of professional skills, such as data analysis, algorithm design, and critical thinking, to ensure the reliability and relevance of the results. While the ethical aspects of the research may not be directly evident, the focus on sustainability and responsible technological development inherently involves ethical considerations, such as resource conservation and minimizing negative impacts on society and the environment. The findings contribute to the development of energy-efficient IoT networks and serve as a foundation for further exploration into power optimization techniques, encouraging the expansion of sustainable IoT ecosystems.

**Keywords:** Thread mesh network, parameter optimization, power optimization, transmission power, MOOD-Sense.

DECLARATION

I hereby certify that this report constitutes my own product, that where the language of others is set forth, quotation marks so indicate, and that appropriate credit is given where I have used the language, ideas, expressions or writings of another.

I declare that the report describes original work that has not previously been presented for the award of any other degree of any institution.

Signed,

Md Mazedul Islam Khan

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# Chapter 1

# Rationale

## 1.1 Introduction

The research project, titled "Overall Power Optimization of Thread Mesh Wireless Network," is a child project within the broader MOOD-Sense initiative. The MOOD-Sense project employs IoT devices to detect and predict challenging behavior in dementia patients. The project aims to develop an early warning system combining sensors, artificial intelligence, and wireless communication to provide feedback for healthcare professionals and improve patient care and safety [1]. To further enhance the connectivity and scalability among IoT devices in the MOOD-Sense project, a new network protocol called Thread is proposed to be implemented. Thread is a low-power, IPv6-based, mesh networking protocol specifically designed for IoT applications, offering secure, reliable, and efficient communication. It supports self-healing networks with robust routing capabilities and features like end-to-end encryption, making it an ideal choice for the MOOD-Sense initiative [2].

The primary focus of this child project is to optimize the energy efficiency of the wireless Thread network protocol utilized by different wireless sensors and various MOOD-Sense projects. To achieve this, the project examines transmission power network parameter and configuration such as device types, path loss, positions, and RSSI with the objective of determining their optimal configuration.

In order to optimize the transmission power network parameter and reduce overall power consumption, the child project establishes a Thread network and employs an algorithmic approach using appropriate hardware. The ultimate goal is to investigate the impact of transmission power parameter optimization on maintaining reliable communication between devices while minimizing power consumption.

## 1.2 Present Situation

The MOOD-Sense research project originally planned to use three wireless communication technologies: BLE, ZigBee, and Wi-Fi for network communication. However, without a central network protocol, various subprojects within MOOD-Sense, such as dementia patient behavior registration and environmental context monitoring, are being carried out separately. This separation leads to disconnected devices and makes data sharing and integration difficult. The current situation can be visualized as a diagram, showing isolated subprojects and devices without an integrated network.

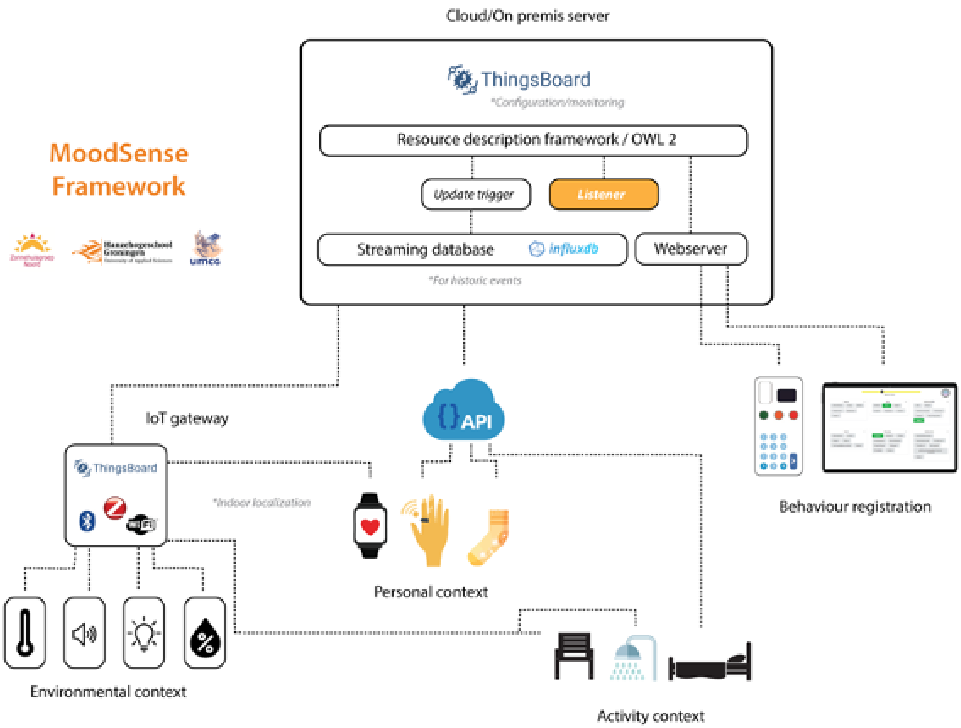


Figure 1.1: Current state of the MOOD-Sense initiative.

To address these challenges and create an energy-efficient network, the proposal to implement a Thread mesh wireless network was introduced. Thread's features, such as mesh networking, multiprotocol support, and low cost, make it an ideal solution for connecting BLE, ZigBee, and Wi-Fi connectivity together. By adopting the Thread mesh network protocol, seamless connectivity, interoperability, and communication among all devices within the MOOD-Sense framework can be achieved. This implementation paves the way for the desired outcome of an optimized, low-power, and reliable network.

## 1.3 Desired Outcome

The desired outcome of this research is to develop an efficient algorithm that integrates seamlessly within the Thread-based wireless network system and optimizing power consumption. This algorithm will not only adjust transmission power but also select the most suitable device types for the network, contributing to energy efficiency and reliable communication. A schematic overview of the system with the integrated algorithm is as follows:

1. **Input**: The primary input parameters for the network optimization algorithm include the total number of devices and the distance between each device. These inputs provide the necessary data to guide the optimization process and ensure that the algorithm makes informed decisions regarding device types and transmission power levels.

2. **Algorithm**: The power optimization algorithm consists of two stages: the Monte Carlo Method and the Genetic Algorithm. In the first stage, MCM focuses on determining the right device types based on various constraints and constructing an optimal network configuration with an initial transmission power setting. The second stage involves GA, which takes the output from MCM and optimizes the transmission power settings to minimize power consumption while maintaining network reliability.

3. **Integration**: The algorithm will run separately on a dedicated system and generate output for optimal device types and transmission power settings. This output will then be manually integrated into the Thread devices, ensuring that the devices are configured for optimal performance based on the algorithm's recommendations.

4. **Optimization**: In the optimization process, the MCM algorithm initially finds the right device types and builds the optimal network configuration with the initial transmission power, considering various constraints. Afterward, the GA algorithm takes this output and optimizes the transmission power settings to make the network as low-powered and energy-efficient as possible, without compromising on reliability.

5. **Output**: The output consists of the appropriate device types for a reliable Thread network configuration, along with the optimal transmission power settings for each device. This output enables the creation of an energy-efficient and reliable Thread-based wireless network that meets the needs of the MOOD-Sense initiative and other similar IoT applications.

By achieving this desired outcome, the algorithm will provide a comprehensive solution for power optimization in Thread networks, supporting the MOOD-Sense initiative and similar IoT applications in building energy-efficient and sustainable networks.

## 1.4 Problem Definition

As the adoption of IoT devices in applications like the MOOD-Sense initiative increases, there is a growing need for energy-efficient and reliable wireless network protocols. The Thread network protocol offers low-power and reliable mesh networking, making it suitable for such applications. However, optimizing power consumption while maintaining network reliability remains a challenge. Additionally, the selection of appropriate device types is crucial for building an efficient Thread network, as Thread offers various device types depending on the use case.

The primary goal of this research is to determine the most effective algorithmic approach for power optimization in a Thread-based wireless network, specifically through transmission power adjustments and the selection of the right device types. By focusing on these aspects, the research will contribute to the development of energy-efficient network solutions for the MOOD-Sense initiative and similar IoT applications. This approach ensures the proper selection and utilization of devices within the Thread network, optimizing the overall network performance and energy efficiency.

## 1.5 Research Questions

### Main Research Question

How can parameter optimization be applied to develop a power-optimized Thread mesh wireless network?

### Sub-Research Questions

1. What are the key features of the Thread protocol that make it suitable for IoT applications, specifically in the context of the MOOD-Sense project?

2. Which parameters significantly impact the transmission power in a Thread network, and how do they relate to energy efficiency and network performance?

3. How do the Monte Carlo Method (MCM) and the Genetic Algorithm (GA) differ in their approach to optimizing transmission power in a Thread network, and what are the key steps for their implementation?

4. What are the specific hardware requirements for implementing a Thread network, and how do they influence the network's energy efficiency and performance in the context of power optimization?

5. How do variations in algorithmic parameters impact the performance of MCM and GA in optimizing wireless network transmission power and path loss?

6. Are there any differences in power optimization performance between different iterations for both Maximum and Optimized modes?

7. How do the different devices perform in terms of power optimization when comparing the Maximum and Optimized modes?

8. Is there a correlation between mean, max, and min current values and the efficiency of power optimization for both Maximum and Optimized modes?

9. How does the location impact the power optimization performance of the Maximum and Optimized modes?

10. How does the performance of the MCM and GA modes differ across different device types, and what impact does this have on current consumption?

11. How do MCM and GA modes compare with Maximum mode in terms of efficiency across various locations and device types?

12. What is the significance of errors in the power optimization process and their impact on the performance of MCM and GA modes?

## 1.6 List of Requirements

Focusing on power optimization in the Thread mesh wireless network protocol and ensuring reliable communication, the following requirements address the challenges related to power consumption and sustainability in Thread mesh wireless networks and guide the research process:

1. Optimize power efficiency for the Thread network protocol with a focus on minimizing power consumption while maintaining reliable communication.
   **Constraint**: The optimization should not compromise the network's stability or communication quality.

2. Apply Monte Carlo and Genetic Algorithm for optimizing transmission power and determining efficient network configurations.
   **Constraint**: The optimization techniques should be computationally feasible and should not add significant overhead to the network's operation.

3. Develop a power-optimized Thread mesh wireless network by considering the optimal device types for different nodes.
   **Constraint**: The selected device types should maintain low power consumption while meeting the network's performance requirements.

4. Assess the impact of location on power optimization performance for both Maximum and Optimized modes.
   **Constraint**: The assessment should consider diverse environments to ensure the results are applicable to various real-world situations.

5. Compare the performance of MCM and GA modes across different device types and locations in terms of power optimization.
   **Constraint**: The comparison should be fair and unbiased, taking into account the specific characteristics of each device type and optimization technique.

6. the significance of errors in the power optimization process and their impact on the performance of MCM and GA modes.
   **Constraint**: The investigation should identify potential sources of errors and recommend ways to minimize their impact on power optimization performance.

7. Suggest future research directions and improvements for Thread network optimization, including device positioning, path loss, and broader application scope.
   **Constraint**: The suggestions should be realistic and feasible, considering existing limitations and challenges in the field.

8. Ensure the research adheres to responsible research and innovation principles, including ethical aspects, professional skills, applied research, and sustainability.
   **Constraint**: The research should prioritize the development of sustainable solutions and maintain transparency and accountability throughout the process.

# Chapter 2

# Situational & Theoretical Analysis

## 2.1 The Thread Protocol

Thread is a low-power, wireless IoT protocol designed to provide secure, reliable, and scalable networking for connected devices. Developed by the Thread Group, which includes notable members such as Nest Labs (a subsidiary of Google), ARM, and Silicon Labs, Thread was introduced in 2014 to address the growing need for a standardized and efficient IoT networking solution. Built on open standards, Thread is an IPv6-based protocol that utilizes the IEEE 802.15.4 radio standard for communication, making it compatible with a wide range of existing devices and technologies [3].

### 2.1.1 Architecture and Components

Thread's architecture is based on a mesh topology, allowing devices to communicate directly with each other, bypassing the need for a central hub or router. This mesh design enhances network resilience, as devices can automatically re-route communication through alternative paths if a connection is lost. The key components of the Thread protocol include [3]:

1. **Border routers**: These devices serve as gateways between the Thread network and external IP networks, such as Wi-Fi or Ethernet networks. They manage network access, security, and routing of data between the Thread network and other networks.

2. **Leader routers**: They play a vital role in managing the network by assigning addresses to devices, coordinating routing updates, and maintaining overall network stability.

3. **Routers**: These devices are responsible for routing data within the Thread network. They can also act as parent devices to other devices within the network, providing connectivity to devices with limited routing capabilities.

4. **End devices**: These devices communicate directly with their parent routers and are typically low-power devices, such as sensors or actuators. End devices do not participate in routing or network management.

5. **Links**: Thread networks use links to establish connections between devices, allowing them to communicate and exchange data. Links are essential for maintaining the mesh topology of Thread networks.

Figure 2.1 shows a visual representation of the basic Thread network topology, which includes all the listed components. By combining these components, the Thread network architecture provides a robust, scalable, and energy-efficient solution for IoT applications, including the MOOD-Sense project.

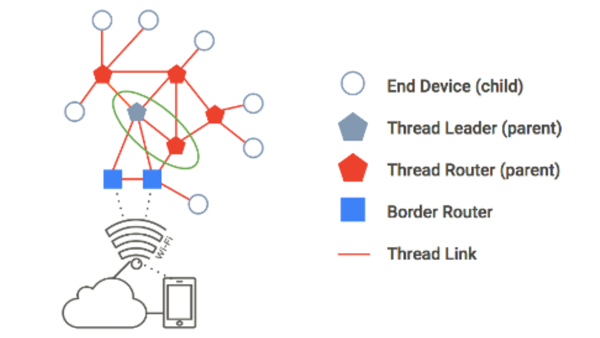


Figure 2.1: Basic Thread network topology.

### 2.1.2 Key Features and Advantages

Considering the specific requirements of various IoT applications, including the MOOD-Sense project, the following features and advantages of Thread make it a suitable choice [3]:

1. **Low power consumption**: Thread's energy-efficient design aligns with the need for long battery life in devices that continuously monitor, collect, and transmit data in various IoT scenarios.

2. **Scalability**: The mesh topology of Thread networks allows for the seamless addition of new devices, enabling IoT projects to adapt and expand as needed.

3. **Security**: Thread's end-to-end encryption and secure commissioning processes ensure that communication between devices is protected, maintaining data privacy and security across diverse applications.

4. **Robustness and reliability**: Thread's self-healing mesh network design ensures reliable and resilient communication, which is crucial for continuous monitoring and data collection in IoT applications.

5. **Interoperability**: Thread's open standards ensure compatibility with a wide range of devices and technologies, allowing IoT projects to integrate various sensors, devices, and communication technologies within a single, unified network.

Overall, the Thread protocol's features address the key question of its suitability for IoT applications in various contexts, including the MOOD-Sense project. Offering a secure, reliable, and energy-efficient networking solution, Thread meets the requirements for continuous monitoring, improved data collection, and seamless integration across industries.

## 2.2 Power Optimization

Optimizing power consumption in wireless IoT networks is a critical challenge, particularly for applications like the MOOD-Sense project, where devices are expected to operate for extended periods without frequent battery replacements or recharging. One effective approach to reduce power consumption is by minimizing transmission power while still maintaining reliable communication among devices, taking into account factors such as path loss and signal strength [4]. This section describes the implementation of transmission power control for Thread wireless networks, aiming to optimize the overall power consumption and ensure efficient and reliable communication among devices within the MOOD-Sense project context.

### 2.2.1 Factors Influencing Transmission Power

Parameters influencing transmission power in a Thread network are crucial for optimizing energy efficiency and network performance. By examining these factors, network designers can make informed decisions to achieve optimal performance under various conditions. A thorough understanding of these parameters is essential for implementing effective power management strategies and maintaining reliable communication within the network. Some of the factors include:

#### Distance

The distance between devices directly influences the transmission power, as a longer distance between devices typically results in higher path loss. Therefore, devices that are farther apart may require higher transmission power levels to maintain a stable connection. The Euclidean distance matrix calculates the distance between pairs of devices. The distance between devices $i$ and $j$ with coordinates $(x1, y1)$ and $(x2, y2)$ is calculated as follows:

$$distance\,(i,j) = \sqrt{(x^2 - x^1)^2 + (y^2 - y^1)^2} \tag{2.1}$$

This calculation helps account for spatial constraints and device placements, ensuring Monte Carlo random input generation considers these factors for a more efficient and optimized Thread network [5].

### Received Signal Strength Indicator

Received Signal Strength Indicator (RSSI) is a measurement of the power level of a received radio signal. It helps to determine the link quality between devices in a wireless network. A higher RSSI value indicates a stronger received signal, which may require lower transmission power to maintain reliable communication [6]. The RSSI calculation, including transmit and receive antenna gains, is:

$$RSSI = P_t + G_t + G_r - L_p \tag{2.2}$$

Where $RSSI$ represents the Received Signal Strength Indicator ($dBm$), $P_t$ is the Transmission Power ($dBm$), $G_t$ is the Transmit Antenna Gain ($dBi$), $G_r$ is Receive Antenna Gain ($dBi$), and $L_p$ is Path Loss ($dB$) [7].

Thread devices typically have an RSSI sensitivity of -100 $dBm$. This formula applies to uplink and downlink connections, offering a more accurate signal strength representation and aiding in network performance optimization and energy consumption [8].

### Antenna Gain

The gain of the antennas used in the network can also affect the transmission power. A higher gain antenna can focus the radio signal more effectively, requiring less transmission power to achieve the same signal strength at the receiver [9].

### Path Loss

Path loss refers to the attenuation of the radio signal as it propagates through the environment. It depends on factors such as the distance between transmitter and receiver, frequency, and environmental conditions. Path loss has a significant impact on the transmission power required to maintain reliable communication. This research analyzes three key path loss models and their applications in wireless communication systems.

**Free-Space Propagation Model** The free-space propagation model is used for predicting the received signal strength in line-of-sight (LOS) environments, where there are no obstacles between the transmitter and receiver. It is often adopted for satellite communication systems. The Friis equation 2.3 describes the received power at distance $d$, considering non-isotropic antennas with transmit gain $G_t$ and receive gain $G_r$ [10]:

$$P_r\left(d\right) = \frac{P_t G_t G_r \lambda^2}{\left(4\pi\right)^2 d^2 L} \tag{2.3}$$

Where $P_t$ represents the transmit power $(w)$, $d$ is the distance between transmitter and receiver $(m)$, $\lambda$ is the wavelength of radiation $(m)$, $G_t$ is transmit gain $(dB)$, $G_r$ receive gain $(dB)$, and $L$ is the system loss factor independent of the propagation environment. The free-space path loss $PL_F(d)$ can be directly derived without any system loss from equation 2.3:

$$PL_F(d)\,[dB] = 10log\left(\frac{P_t}{P_r}\right) = -10log\left(\frac{G_t G_r \lambda^2}{(4\pi)^2 d^2}\right) \tag{2.4}$$

Without antenna gains (i.e., $G_t = G_r = 1$), equation 2.4 is reduced to:

$$PL_F(d)\,[dB] = 10log\left(\frac{P_t}{P_r}\right) = 20log\left(\frac{4\pi d}{\lambda}\right) \tag{2.5}$$

**Log-Distance Path Loss Model** The log-distance path loss model is a more generalized approach, accounting for the varying path loss exponent $n$ depending on the environment. The path loss at distance $d$ is given by equation 2.6, where $d_0$ is the reference distance at which the path loss inherits the characteristics of free-space loss [10]:

$$PL_{LD}(d)\,[dB] = PL_F(d_0) + 10nlog\left(\frac{d}{d_0}\right) \tag{2.6}$$

Where $d_0$ is a reference distance and $n$ corresponds to free space which tends to change as shown in the following table.

Table 2.1: Path loss exponent for different environments.

| Environment | Path Loss Exponent $(n)$ |
|---|---|
| Free space | 2 |
| Urban area cellular radio | 2.7 - 3.5 |
| Shadowed urban cellular radio | 3 - 5 |
| In building line-of-sight | 1.6 - 1.8 |
| Obstructed in building | 4 - 6 |
| Obstructed in factories | 2 - 3 |

The path loss exponent $(n)$ varies based on the environment, as shown in table 2.1, and helps to adjust the log-distance path loss model for more accurate predictions. Lower values represent environments with fewer obstructions, such as free space, while higher values indicate more complex environments with buildings or other obstacles.

**Log-Normal Shadowing Model** The log-normal shadowing model considers the random nature of shadowing effects, making it more suitable for realistic situations. The model is given by equation 2.7, where $X_\sigma$ is a Gaussian random variable with a zero mean and a standard deviation of $\sigma$:

$$PL\left(d\right)\left[dB\right] = \overline{PL}\left(d\right) + X_{\sigma} = PL_{F}\left(d_{0}\right) + 10nlog\left(\frac{d}{d_{0}}\right) + X_{\sigma} \tag{2.7}$$

In other words, this particular model allows the receiver at the same distance $d$ to have a different path loss, which varies with the random shadowing effect $X_{\sigma}$ [10].

#### Device Types

In a Thread network, devices can have different types and roles, such as routers, end devices, or border routers. These roles can impact the transmission power requirements, as routers may need to communicate with multiple neighboring devices, whereas end devices only need to communicate with their parent router [3].

### 2.2.2 Algorithmic Approaches

To optimize transmission power in a Thread network, algorithmic approaches can be employed. In this research, two algorithms are used to address transmission power optimization: the Monte Carlo Method (MCM) and the Genetic Algorithm (GA). The MCM focuses on selecting the right device types and configuring an optimal network based on the constraints and requirements of the MOOD-Sense project. The GA, on the other hand, takes the output from the MCM and optimizes the transmission power settings for each device, ensuring minimal energy consumption while maintaining network performance.

#### Monte Carlo Method

The Monte Carlo Method (MCM) is a statistical method that uses random sampling and repeated computation to obtain numerical results. In the context of transmission power optimization, MCM will be used to generate random sets of device types, positions, and transmission powers, evaluate their performance, and identify the most suitable configuration for the Thread network [11]. The steps for implementing MCM in this research are as follows:

1. Define the parameter space, including the range of values for each parameter involved in the network configuration.

2. Generate a large number of random configurations within the parameter space.

3. Evaluate the performance of each configuration using predefined constraints, such as types of devices.

4. Identify the configuration that satisfies the constraints and use it as the initial configuration for the GA.

**Genetic Algorithm**

The Genetic Anglrothm (GA) is an optimization technique inspired by the process of natural selection. It uses a population of possible solutions and evolves them over time using genetic operators, such as mutation and crossover. In this research, GA will be used to further refine the initial configuration obtained from MCM and find the optimal transmission power for each device in the Thread network [12]. The steps for implementing GA in this research are as follows:

1. Initialize the population with the best configuration obtained from MCM.
2. Evaluate the fitness of each individual in the population based on the predefined constraints.
3. Select the fittest individuals for reproduction using selection techniques, such as tournament selection or roulette wheel selection.
4. Apply genetic operators (crossover and mutation) to generate offspring from the selected parents.
5. Replace the least fit individuals in the population with the offspring.
6. Repeat steps 2 to 5 for a predefined number of generations or until a convergence criterion is met.
7. Obtain the final optimal configuration from the fittest individual in the population.

By combining MCM and GA, the proposed algorithmic approach efficiently explores the parameter space and identifies the optimal configuration that minimizes power consumption while maintaining network performance and reliability in the Thread network. Addressing the sub-research question 3, this research demonstrates the effectiveness of the combined approach in achieving the desired outcomes.

### 2.2.3 Step-by-Step Guide for Power Optimization

1. **Identify the influencing factors and parameters**: Determine the parameters that impact transmission power, such as distance between devices, path loss, signal strength, interference, and device types.
2. **Develop the algorithms**: Implement the MCM and GA algorithms to address power optimization in the Thread network, considering the constraints and requirements of the MOOD-Sense project.
3. **Determine optimal device types and network configuration**: Use the MCM to identify the appropriate device types and optimal network configuration for the Thread network.

4. **Optimize transmission power settings**: Apply the GA to optimize the transmission power settings for each device in the network, ensuring minimal energy consumption while maintaining reliable communication.

5. **Evaluate network performance**: Assess the overall performance of the Thread network, ensuring that the optimized power settings do not compromise the network's reliability or efficiency.

6. **Iterate and refine**: Continuously refine the algorithms and network configuration as necessary to maintain optimal power consumption and network performance.

Through exploring the factors influencing transmission power and employing algorithmic approaches, this research seeks to provide a comprehensive understanding of power optimization in a Thread network and its implications on energy efficiency and network performance in the context of the MOOD-Sense project.

## 2.3 Hardware Analysis

In this research, several hardware components were employed to implement and optimize the Thread network for power efficiency. Each hardware piece played a crucial role in different stages of the project:

### 2.3.1 nRF52840 Development Kit

The nRF52840 Development Kit (DK) is a versatile single-board development kit for Bluetooth 5, Bluetooth mesh, Thread, Zigbee, 802.15.4, ANT, and 2.4 $GHz$ proprietary applications on the nRF52840 SoC. In this research, the nRF52840 DK was used to develop and test the Thread network, acting as routers and end devices in the network topology. The development kit enabled the research team to implement and evaluate the network performance and power consumption under different configurations [13].

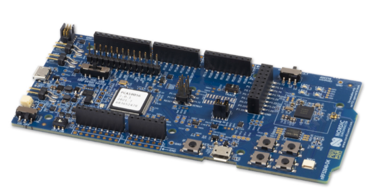

Figure 2.2: nRF52840 Development Kit.

### 2.3.2 nRF52840 Dongle

The nRF52840 dongle is a small, low-cost USB device for the nRF Connect for Desktop PC tool. It supports Bluetooth 5, Bluetooth mesh, Thread, Zigbee, 802.15.4, ANT, and 2.4 GHz proprietary protocols. In the research, the dongle was used to extend the network by adding more nodes, facilitating the evaluation of scalability and network performance in larger network configurations sources [14].

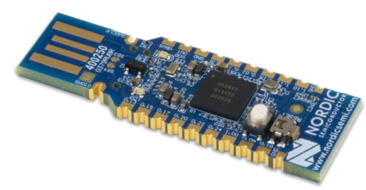

Figure 2.3: nRF52840 Dongle.

### 2.3.3 Power Profiler Kit II

The Power Profiler Kit (PPK) II is an easy-to-use tool for measuring and optimizing the power consumption of IoT devices. In this research, the Power Profiler Kit II was utilized to measure the power consumption of the nRF52840 DK devices in various network configurations, enabling the research to assess the energy efficiency of the network and identify areas for improvement [15].

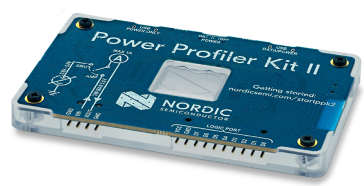


Figure 2.4: Power Profiler Kit II.

### 2.3.4 Raspberry Pi 4

The Raspberry Pi 4 model B is a single-board computer used for various applications, including IoT development. In this research, the Raspberry Pi 4 served as a border router and provided an interface between the Thread network and external networks. The Raspberry Pi 4 allowed the research to evaluate the overall network performance and data exchange with external systems [16].

Figure 2.5: Raspberry Pi 4 model B.

By understanding the roles of each hardware component in the research, it becomes evident how they collectively contributed to the successful implementation and optimization of the Thread network for power efficiency.

### 2.3.5 Constraints and Limitations

Using these hardware components poses certain constraints and limitations on the research, with some potential consequences:

1. **Limited scalability**: The number of available nRF52840 DK and nRF52840 Dongle devices may limit the size of the network being optimized, potentially affecting the generalizability of the results. This limitation might make it challenging to extrapolate the findings to larger networks or different device types.

2. **Hardware-specific performance**: The optimization results might be influenced by the specific hardware used, such as the nRF52840 DK and nRF52840 Dongle, and may not be directly applicable to other devices or platforms. As a consequence, further research and testing may be required to confirm the findings' applicability in different hardware contexts.

3. **Measurement accuracy**: The accuracy of the Power Profiler Kit II may impact the precision of the power consumption measurements, potentially affecting the optimization results. This limitation could lead to underestimation or overestimation of energy savings, influencing the overall conclusions regarding the network's energy efficiency.

These hardware-related challenges could influence the research outcomes, making it essential to be aware of the limitations and consider their potential impact on the findings when interpreting the results and applying them to real-world scenarios.

### 2.3.6 Implications for Wireless Network Technology Development

Taking into account the hardware constraints and limitations, the implications for wireless network technology development in the context of this research can be examined. The chosen hardware components, such as the nRF52840 DK, and nRF52840 Dongle directly impact the energy efficiency, performance, and scalability of the Thread network. Using these components enabled the investigation and optimization of power consumption and network performance. However, it is essential to acknowledge that hardware limitations might pose challenges when adapting the network to various IoT applications or scaling it to larger configurations. By addressing the sub-research question 4, this study highlights the importance of hardware selection and its implications for future wireless network technology development.

## 2.4 Literature Research

Thread network power consumption research has been limited but offers promising results. One study by Semiconductor [17] demonstrates that the battery life of a Thread node is heavily dependent on the network configuration. For example, a node with an idle current of 3 $\mu A$ and a transmit current of 17 $mA$ can last up to 10 years in a network with a low data rate of 250 *kbps* and a small number of packets per day. However, in a network with a high data rate of 1 $Mbps$ and many packets per day, the same node would only last for a few months. A white paper by Group [18] provides noteworthy results on the power consumption and optimization of Thread networks, showing that the Thread protocol could achieve a standby power consumption of less than 3 $mW$, with typical transmit and receive power consumption ranging between 15 $mW$ and 20 $mW$. The study also demonstrated that devices on a Thread network could achieve up to 10 years of battery life when transmitting once per minute, making Thread a strong candidate for low-power IoT applications. Another research effort, conducted by Azoidou, Pang, Liu, *et al.* [19] analyzed the power consumption of Thread end devices, routers, and coordinators. The study demonstrated that enabling power management features could reduce power consumption by up to 70% in sleep mode. Additionally, two power optimization techniques, dynamic power management and dynamic voltage and frequency scaling, were evaluated, with the latter having a greater impact, reducing consumption by up to 35%. The research also emphasized that power consumption is influenced by transmission power level, data rate, and routing topology and suggested that implementing optimization techniques could reduce power consumption by up to 70%.

In the paper by Sheth and Han [4] presents a practical implementation of transmit power control for 802.11b wireless networks. They focus on optimizing transmit power to reduce power consumption while maintaining correct reception of packets. The researchers achieved a maximum power savings of 25%, including idling power, by implementing their adaptive transmit power control algorithm as a user-level application layer process. This work is relevant to power optimization strategies in IoT applications, such as Thread networks. Behzad and Rubin [20] investigate the impact of transmission power on the throughput capacity of finite ad hoc wireless networks using a scheduling-based MAC protocol in their paper, such as TDMA. The authors demonstrate that by properly increasing the nodal transmit power level, the capacity of an ad hoc wireless network can be maximized, regardless of nodal distribution and traffic pattern. The primary finding is that higher transmission power contributes to increased combinatorial diversity, optimizing joint scheduling and routing schemes, which is valuable for the development of efficient IoT applications using protocols like Thread.

In the realm of algorithm optimization, the Monte Carlo method (MCM) is a robust, efficient, flexible, and scalable tool used across various fields, including science, finance, and engineering. Research by Kroese, Brereton, Taimre, *et al.* [11] emphasizes MCM's popularity and its applications in areas like industrial engineering, operations research, physical processes, random graphs, finance, biology, medicine, and computer science. The authors highlight MCM's simplicity, strength in randomness, and theoretical justification. On the other hand, Genetic Algorithm (GA) is a heuristic optimization algorithm that handles non-linear, non-convex, and intermittent problems. It is widely applied in various engineering and scientific applications. One study by Ferentinos, Tsiligiridis, and Arvanitis [21] employs GA to optimize wireless sensor networks (WSNs) for precision agriculture applications. The research determines active sensors, cluster heads, and signal ranges while considering network connectivity, energy conservation, and application requirements. Results indicate that GA-generated designs outperform random deployments regarding connectivity and energy consumption. Norouzi and Zaim [22] explore the potential of GA in optimizing the operational stages of WSNs, discussing node placement, network coverage, clustering, data aggregation, and routing. Simulations demonstrate that GA-based approaches outperform existing protocols, suggesting that GA can optimize WSNs in military, medical, and commercial applications.

In summary, although the literature on Thread power optimization is limited, the results from existing studies suggest that the protocol has significant potential for reducing energy consumption in low-power wireless networking applications. More research is needed to fully understand and optimize the power consumption of Thread networks in large-scale deployments. Meanwhile, MCM and GA have significantly influenced quantitative problem-solving across numerous research fields, becoming indispensable tools for understanding complex systems and optimizing parameters in various applications. However, their computational complexity increases with the number of parameters, making it challenging to apply to large-scale problems.

# Chapter 3

# Conceptual Model

The Conceptual Model section describes the research focusing on power optimization in Thread mesh wireless networks as part of the MOOD-Sense initiative. The primary goal is to improve energy efficiency in IoT applications utilizing the Thread protocol. The project will investigate and evaluate power optimization techniques and their impact on the overall network performance, contributing to the development of energy-efficient IoT networks.

The system will be developed based on the Thread protocol, a low-power, IPv6-based networking protocol designed for IoT applications. To optimize the power consumption of Thread networks, the project will employ a two-step process. First, the Monte Carlo Method will be used to find the optimal network configuration and initial transmission power. This step will involve a thorough analysis of different network configurations based on different constraints. The project will leverage MCM's strengths in randomness and theoretical justification to ensure the reliability of the results. Next, the Genetic Algorithm will take the final output from MCM and focus on finding the lowest transmission power possible. The use of GA will help improve the overall energy efficiency and performance of the Thread network by taking into account the network's constraints. The following diagram illustrates the flow of the entire process, from MCM and GA optimization to the implementation of optimized transmission power in the Thread network that shows a clear visual representation of the project's methodology.

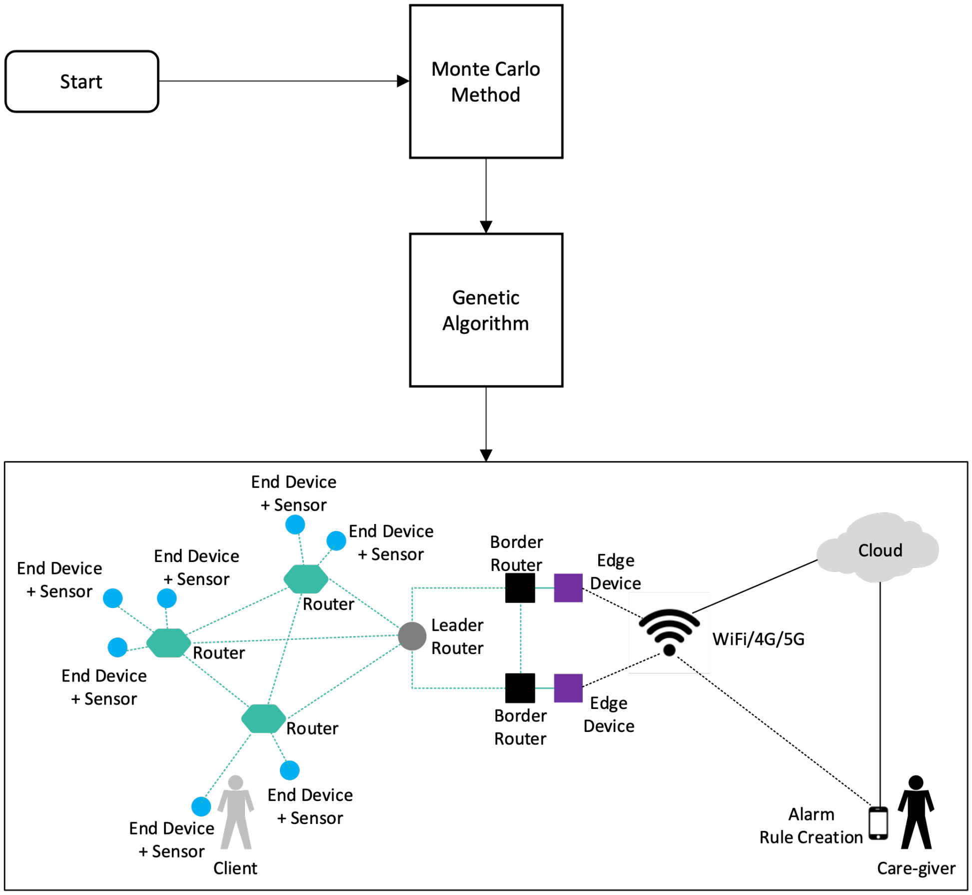


Figure 3.1: Thread network power optimization conceptual model.

The project will consider the cost of hardware components, software development, testing, and deployment while maintaining a balance between cost-effectiveness and performance. The power consumption will be measured using Power Profiler Kit II explained in hardware section. The research will measure output power in different scenarios to validate the effectiveness of the power optimization techniques employed. These scenarios will be categorized based on the method, location, type, mode, duration, and ping used for power optimization and measurement.

1. **Method**: The power consumption will be measured in two primary scenarios - Maximum and Optimized. The Maximum scenario represents the baseline power consumption, where no optimization techniques are applied. The Optimized scenario will measure power consumption after implementing the MCM and GA optimization techniques.

2. **Location**: The measurements will be conducted in two different locations - Lab and Home. The Lab setting is smaller in size compared to the Home location, allowing for controlled environments and reproducible results. The Home setting provides a

real-world context, with a larger area, helping to understand the performance of the Thread network in everyday IoT applications.

3. **Type**: The power consumption measurements will also be conducted based on the type of network activity. The No Sensor scenario represents a Thread network with no active sensors, while the Ping scenario simulates data exchange between nodes, resembling real IoT network behavior.

4. **Mode**: The project will compare the effectiveness of MCM and GA optimization techniques. The MCM mode will measure power consumption based on network configurations optimized using the Monte Carlo Method. The GA mode will measure power consumption with network configurations optimized using the Genetic Algorithm.

5. **Duration**: The power consumption measurements will be conducted for different durations - 60 seconds in the Lab location and 300 seconds in the Home location. This variation in duration will help in understanding the impact of time on power consumption in different environments.

6. **Ping**: In the Lab location, 50 pings will be sent within the 60-second duration, whereas in the Home location, 290 pings will be sent during the 300-second duration. This distinction will help analyze the impact of network activity on power consumption in both controlled and real-world settings.

By measuring power consumption in these different scenarios, the research will provide a comprehensive understanding of the power optimization techniques' effectiveness. The results will be analyzed to draw comparisons and determine the optimal approach for power consumption reduction in Thread networks, ultimately contributing to the development of energy-efficient IoT networks.

In terms of sustainability, the research will emphasize energy-efficient hardware and power optimization techniques to minimize environmental impact, leading to sustainable IoT network deployments. By focusing on energy efficiency, the project inherently follows sustainable work principles, addressing resource conservation and minimizing negative impacts on society and the environment. Moreover, the research process involves the application and development of professional skills, such as data analysis, algorithm design, and critical thinking, to ensure the reliability and relevance of the results.

By combining the use of MCM and GA to optimize power consumption in Thread networks and employing sustainable work principles, this project will contribute valuable insights to the field of energy-efficient IoT network design and implementation.

# Chapter 4

# Research design

## 4.1 Mathematical Constraints

The objective of the mathematical model is to build a Thread network that adheres to specific mathematical constraints, ensuring a well-functioning network with the optimum device types, sensitivity, and RSSI. By complying with the constraints, the Thread network can be effectively optimized for both performance and energy consumption. The constraints of the model are as follows:

1. To establish a link between the sensors and EDs, the RSSI of each end device must be approximately above the sensitivity of each ED. This ensures a stable connection between the devices [9].

2. The transmission power limitation, ranging from -20 dBm to 8 dBm, is set according to the hardware specifications of the devices in the Thread network, ensuring optimal performance while facilitating power optimization techniques within these constraints for energy efficiency [8].

3. The number of REEDs must be equal to the number of routers and the leader because, if a router is lost, a connected REED must become a router to replace the dead router and maintain network resilience.

4. To establish a connection between the EDs and routers, the RSSI of each router must be approximately above the sensitivity of each router. This guarantees a stable link between the devices and the routers [9].

5. To establish a connection between the routers and border routers, the RSSI of each border router must be approximately above the sensitivity of each border router, ensuring a reliable link between the network components [9].

The following mathematical model is designed for this purpose:

$$Min \sum_{i=1}^{M} P_t^i \tag{4.1}$$

**Subjects to:**

$$\begin{aligned} RSSI_{ED}^{j} > EDSensitivity, j \in 1, \cdots, N \\ -20dBm \leq P_t^j \leq 8dBm \\ N_{REED} = n_{Router} + n_{Leader} \end{aligned} \tag{4.2}$$

$$\begin{aligned} RSSI_{Router}^{k} > RouterSensitivity, k \in 1, \cdots, O \\ -20dBm \leq P_t^k \leq 8dBm \end{aligned} \tag{4.3}$$

$$\begin{aligned} RSSI_{BD}^{L} > BDSensitivity, L \in 1, \cdots, P \\ -20dBm \leq P_t^L \leq 8dBm \\ Sensitivity = -100dBm \\ SEED \in 0, 1 \\ n_{Leader} = 1 \\ n_{Router} + n_{Leader} \geq 3 \\ n_{BR} = 2 \end{aligned} \tag{4.4}$$

Where $P_t$ represents the Transmit Power of each one of the $M$ devices, $RSSI$ is the Received Signal Strength Intensity, $ED$ is End Device, $REED$ is Router Eligible End Devices, $N_{REED}$ is the number of the REEDs, $n_{Router}$ is the number of the routers, $n_{Leader}$ is number of the leaders, $N$ is amount of end devices, $O$ is the number of Routers, $P$ is the number of Border Routers, $SEED$ is Sleepy End Devices, and $Sensitivity$ is $-100dBm$ with IEEE 802.15.4 [13].

## 4.2 Monte Carlo Method Process

The Monte Carlo Method involves four main steps. First, the process is initialized with predefined parameters and constraints. Second, random numbers are generated within the defined bounds to explore various network configurations. Third, the generated configurations are evaluated based on their performance and adherence to constraints. Finally, after a predetermined number of iterations or reaching an acceptable solution, the MCM process comes to an end, providing an optimized network configuration. For a detailed explanation of each step, refer to the respective sections below.

### 4.2.1 Initialize

The Monte Carlo method is initiated to optimize the Thread network, considering the key parameters influencing the network's performance and energy efficiency. These parameters are outlined in the table below:

Table 4.1: Parameters influencing Monte Carlo Method.

| Param | Description |
|---|---|
| $N_d$ | The total number of devices participating in the network, which is set to 8 for this research, representing a small-scale IoT network. |
| $P_{tx}$ | Determines the signal strength for each device, randomly generated in a range between -20 $dBm$ and 8 $dBm$ according to the mathematical constraints, affecting network connectivity and energy consumption. |
| $F_c$ | The carrier frequency used for calculating RSSI using the general path loss model, set at 2.4 $GH_z$, based on Thread protocol specification. |
| $D_0$ | A reference distance of 0.25 $m$, associated with the carrier frequency $F_c$, employed in the path loss model to calculate signal attenuation. |
| $d$ | Represents the distance between two devices in the network, as illustrated in figures 4.3 and 4.4, influencing the strength of the signal received by devices. |
| $n$ | The path loss exponent, set to 5.0, which represents the rate at which the signal power decays with distance in the path loss model. |
| $\sigma$ | The variance of the shadowing component, set to 3.0 $dB$, accounts for signal fluctuations due to obstacles and multipath propagation in the environment. |
| $G_t$ | The transmit antenna gain, set to 0.0 $dB$, which reflects the effectiveness of the transmitting antenna in directing the radio waves towards the receiving device. |
| $G_r$ | The receive antenna gain, set to 0.0 $dB$, indicating the receiving antenna's ability to capture incoming radio waves. |

### 4.2.2 Generate Random Numbers

Based on the factors mentioned at the start, MCM generates a vector $X$ of length equal to $2n$, where $n$ is the number of places where network elements can be allocated [20]. The vector is represented as:

$$\begin{aligned} X = [x_1, x_2, x_3, \cdots x_n, p_1, p_2, p_3, \cdots, p_n] \\ for\ x_n \in 0, 1, 2, 3, 4, 5 \\ p_n \in -20 : 4 : 8\ dBm \end{aligned} \tag{4.5}$$

Where 0 represents no element allocated, 1 is allocate a SEED, 2 is allocate a REED, 3 is allocate a Router, 4 is allocate the Leader, and 5 is allocate a Border Router.

### 4.2.3 Evaluate Results

The objective function aims to build a Thread network using the optimal network configuration without violating the mathematical constraints. If a constraint is violated, a penalty is added to the objective function, which is weighted according to the importance of the constraint. The objective function with penalty values can be written as:

$$Min \sum_{i=1}^{M} P_t^i + penal_1 + penal_2 + penal_3 \ldots + penal_{nr} \tag{4.6}$$

Where $penal_1$ represents penalty for violating the first restriction, $penal_2$ is penalty for violating the second restriction, and $penal_{nr}$ is the penalty for violating the last restriction.

### 4.2.4 Termination

The MCM converges on an optimal solution that satisfies necessary constraints, providing outputs such as device types, transmission power, and position. It also offers information on constraint violations, including the penalty, power consumption, and RSSI sensitivity violations—these outputs aid in understanding the optimization process and refining the network design. For a comprehensive understanding of the four steps of the MCM process, refer to the following pseudocode, which provides an overview of the algorithm's structure and logic.

**Algorithm 1** Monte Carlo Method pseudocode for network optimization.

Initialize MCM parameters: $N_d$, $d$, $F_c$, $D_0$, $n$, $\sigma$, $G_t$, $G_r$
**while** network **do**
  devices, txpower, position ← generate_random_numbers($N_d$)
  penalty, path_loss, rssi_uplink, rssi_downlink ← mathematical_constraints_evaluation($N_d$, $d$, $F_c$, $D_0$, $n$, $\sigma$, $G_t$, $G_r$)
  **if** penalty is False **then**
    network ← False
  **end if**
  **return** devices, txpower, penalty, path_loss, rssi_uplink, rssi_downlink
**end while**

It is a simplified version of the Monte Carlo Method implementation and does not cover all the details of the original code. It is focused on the primary structure and steps of the method for network optimization and initial network build-up transmission power. To access the complete version of the algorithm code, including all implementation details, refer to the appendix 6.2 section.

## 4.3 Genetic Algorithm Process

The Genetic Algorithm process can be summarized into four main steps: initializing population, evaluating fitness, performing selections, and finding the best solution. These steps are designed to optimize transmission power in the network by evolving a population of candidate solutions through generations. In the following paragraphs, each step is discussed in detail.

### 4.3.1 Initialize

The initial steps of the GA process start with creating a random population with the specified population size, representing different possible network configurations. The population is generated based on the parameters set, as shown below:

Table 4.2: Parameters influencing Genetic Algorithm.

| Param | Description |
|---|---|
| Population size | The number of individuals in the population representing different possible network configurations are set to 100 for this research. |
| Population | An initial random population is created with the specified population size and MCM output, which includes device types, transmission power, and device positions, representing different possible network configurations. For instance: [ [3, 5, 2, 5, 1, 5, 0, 0], [-20, 0, 0, -8, 0, -12, 0, -20], [1, 2, 3, 4, 5, 6, 7, 8]]. |
| Max iteration | The maximum number of iterations to be performed by the Genetic Algorithm, for instance, 100 in this research. |
| Mutation rate | The probability of mutation is set at 0.1 for this research, determining the frequency of random changes introduced to the offspring's genetic information during the optimization process, which helps maintain genetic diversity within the population. |
| Selection method | The method used for selecting individuals from the current population to create the next generation, such as roulette wheel selection, tournament, or sorted. In this research, the sorted selection method was utilized. |
| Mutation method | The method used for mutating individuals affect how genetic information is altered during the mutation process. In this research, the swap mutation method was utilized. |

### 4.3.2 Evaluate Fitness

For each candidate in the population, calculate its fitness score. The fitness measures how effectively the configuration optimizes power consumption, considering path loss and

RSSI sensitivity. Lower power consumption results in a higher fitness value, helping the algorithm identify the best individuals for producing the next generation.

### 4.3.3 Selection, Crossover, and Mutation

In this step, parents are selected from the current population based on their fitness values using sorted selection method. This ensures that individuals with higher fitness values have a higher chance of being chosen as parents, promoting the selection of potentially better solutions.

Next, the crossover operation is performed on the selected parents to create offspring by exchanging genetic material between pairs of parents. The crossover process combines the characteristics of parent individuals, allowing the offspring to inherit properties from both parents, which helps explore new potential solutions in the search space.

Finally, the mutation operation introduces small random changes to the offspring's genetic material by flipping bits within a certain probability (mutation rate). This process enhances diversity within the population and helps to prevent the algorithm from converging prematurely to suboptimal solutions by maintaining variation and allowing the exploration of alternative search paths.

### 4.3.4 Population Update and Termination

After the selection, crossover, and mutation processes, the new offspring are evaluated for their fitness. The population is then updated by replacing all individuals in the current population with the newly generated offspring. This step ensures that the best solutions found so far are preserved and that the overall fitness of the population improves over time.

The GA process iterates through the aforementioned steps for a predefined number of iterations. Once the termination criteria are met, the algorithm returns the best solution found throughout the entire evolutionary process, representing the most optimal network configuration discovered by the GA. Refer to the following pseudocode for an algorithmic overview of the Genetic Algorithm process:

**Algorithm 2** Genetic Algorithm pseudocode for transmission power optimization.

Initialize GA parameters: population_size, population, max_iterations, mutation_rate, selection_method
Initialize population: create_random_population(population_size)
**for** each candidate in population **do**
    fitness = evaluate_fitness(candidate)
**end for**
**for** generation in range(max_iterations) **do**
    parents = select_parents(population, selection_method)
    offspring = crossover(parents, crossover_prob)
    offspring = mutate(offspring, mutation_prob)
    **for** each candidate in offspring **do**
        fitness = evaluate_fitness(candidate)
    **end for**
    population = replace_population(population, offspring)
**end for**
best_solution = find_best_solution(population)

The output is a list of optimized transmission power values for each device, along with device types, positions, and penalty values. For a comprehensive understanding of the Genetic Algorithm's implementation, refer to the appendix 6.2 for the complete code.

## 4.4 Experimental Setup

The prototype was built to validate the output from MCM and GA, using the optimal network configuration determined by MCM, which consisted of a total of 8 devices. The setup included 2 border routers, 3 routers (with one of them automatically elected as a leader), and 3 REEDs. The prototype was designed to closely resemble the conceptual model presented earlier in the figure, with the only slight difference being the use of REEDs instead of sensors as the end devices. An image was provided below to illustrate the Thread network topology that had been constructed.

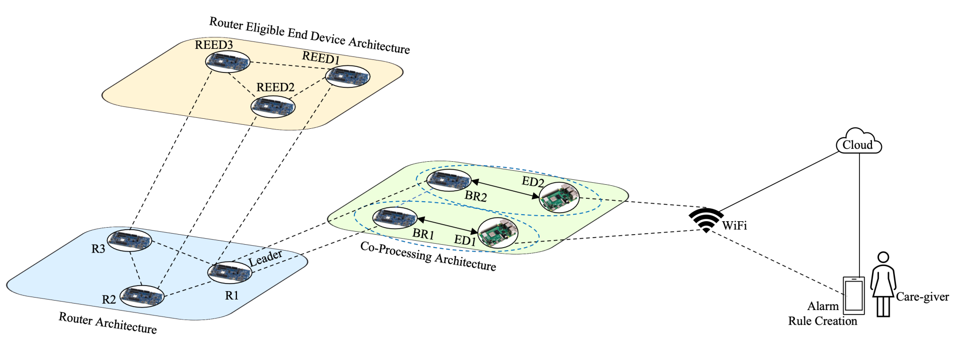


Figure 4.1: Thread network topology of the prototype.

The construction process of the prototype involved several crucial steps, aimed at validating the output from MCM and GA and ensuring optimal network configuration:

1. Customized nRF Thread Client and Server SDK to fit the needs for the research, selecting roles for each device and setting the transmission power output from both MCM and GA for optimal network configuration.

2. Flashed each router with the Thread Server and each REED with the Thread Client customized SDK. In this configuration, routers acted as servers, while REEDs acted as clients. Communication between devices was bidirectional, with the clients having BLE enabled for multiprotocol support.

3. Flashed the border router nodes with the Co-Processor setup provided by nRF. To enable the Raspberry Pi to act as an edge device, the OpenThread Radio Coprocessor (RCP) architecture was implemented.

4. Turned on the devices one by one, noting that the first device activated in the network was most likely to become the leader, although leadership could change during the network's lifetime.

5. Validated all the nodes by running multicast messages using Thread ICMP service. The ICMP service allowed sending echo requests (ping) to devices, activating their Thread antennas. This enabled testing the Thread connection, and devices could also reply [3].

6. Validated the multiprotocol support connection by running a data flow from the ESP32 UWB and mobile devices to the REEDs through BLE, which then forwarded the data to the routers. This step ensured seamless communication between non-Thread devices and the Thread network.

7. Monitored the network for stability and performance, adjusting settings to maintain optimal operation.

Following these steps, the prototype was successfully constructed to apply the optimized settings obtained from the MCM and GA. The subsequent figure presented a real-world Thread network prototype setup from the lab setup. The image provided a clear view of the nRF52840-based Thread nodes, Raspberry Pi as the edge device, and the border router setup with the dongle. It also showcased the development kits used for routers and REEDs.

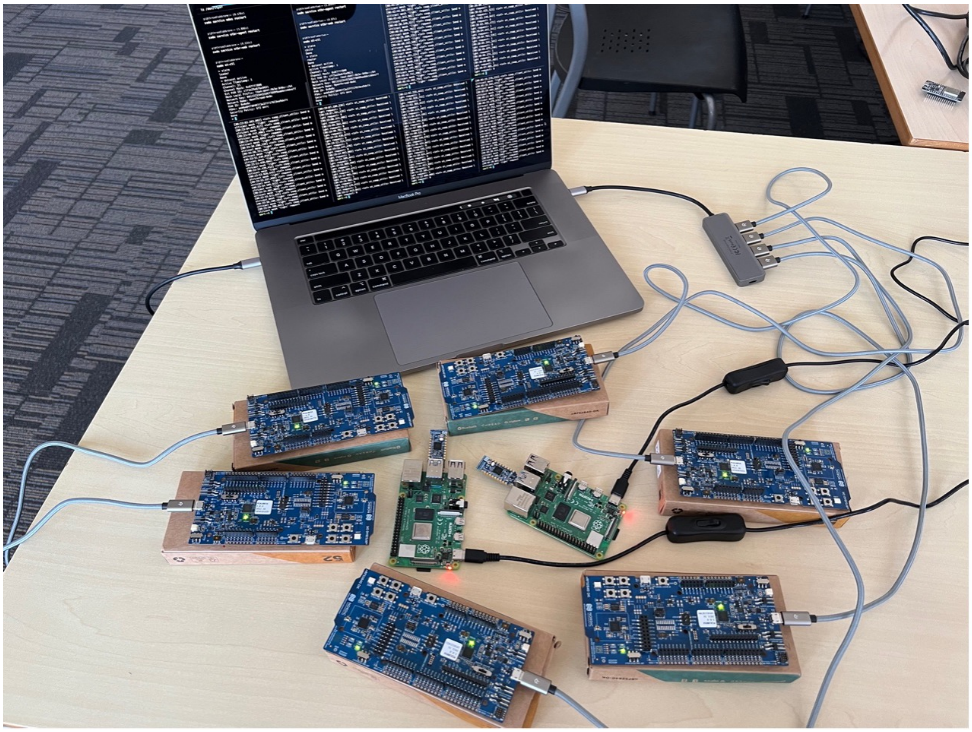

Figure 4.2: Thread network prototype setup in the lab.

## 4.5 Data Collection

The data collection process aimed to validate and compare the solutions from MCM and GA against the maximum mode by measuring power consumption in each device of the built prototype. Utilizing the nRF Power Profiler Kit II, which offers Current (*ma*) measurement at 100,000 samples per second, allowed for accurate power consumption measurements across various scenarios, locations, network activities, optimization modes, and durations. This approach provided insights into the effectiveness of the optimization techniques in both controlled and real-world settings while avoiding excessive data that would have complicated the analysis process.

1. **Method**: Power consumption was measured in two primary scenarios - Maximum and Optimized. The maximum scenario represented the baseline power consumption, where no optimization techniques were applied. The optimized scenario measured power consumption after implementing the MCM and GA optimization techniques.

2. **Location**: Measurements were conducted in two different locations - Lab and Home. The lab setting, smaller in size compared to the home location, allowed for controlled environments and reproducible results. The home setting provided a real-world context with a larger area, helping to understand the performance of the Thread

network in everyday IoT applications. The following images show the Euclidean distance matrix from two different locations to share a clear view of the distance between each device in the two locations.

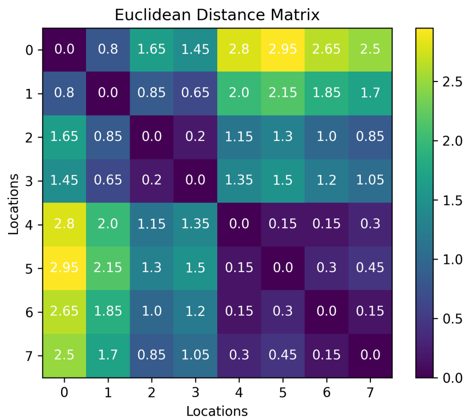


Figure 4.3: Distance matrix for lab.

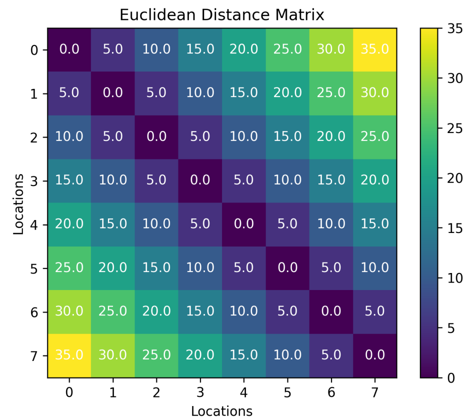


Figure 4.4: Distance matrix for home.

3. **Type**: Power consumption measurements were also conducted based on the type of network activity. The No Sensor scenario represented a Thread network with no active sensors, while the Ping scenario simulated data exchange between nodes, resembling real IoT network behavior [3].

4. **Mode**: The project compared the effectiveness of MCM and GA optimization techniques. The MCM mode measured power consumption based on network configurations optimized using the Monte Carlo Method. The GA mode measured power consumption with network configurations optimized using the Genetic Algorithm.

5. **Duration**: Power consumption measurements were conducted for different durations - 60 seconds in the Lab location and 300 seconds in the Home location. This variation in duration helped in understanding the impact of time on power consumption in different environments.

6. **Ping**: In the lab location, 50 pings were sent within the 60-second duration, whereas in the home location, 290 pings were sent during the 300-second duration. This distinction helped analyze the impact of network activity on power consumption in both controlled and real-world settings.

Following the data collection steps, two images are provided to illustrate the process of collecting power consumption data from the nRF52840 DK using the PPKII. These images offer a visual representation of the setup and the data collection process, giving a clearer understanding of the experimental context and the methods used for obtaining the power consumption measurements.

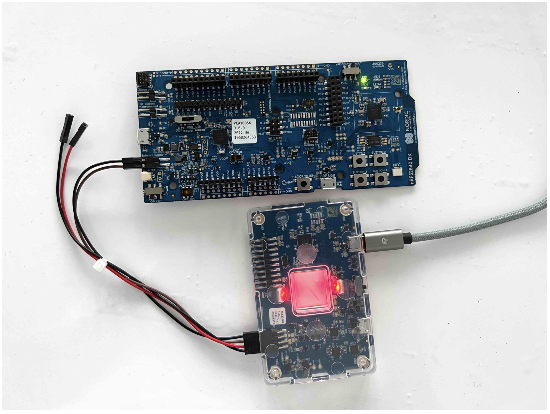

Figure 4.5: PPK II connected to a router.

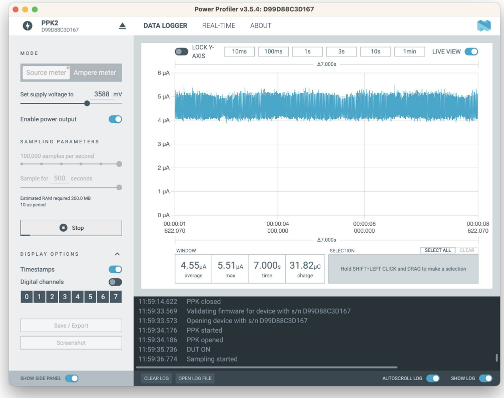


Figure 4.6: PPK II software in source meter mode.

# Chapter 5

# Research Results

## 5.1 Monte Carlo Method Analysis

The Monte Carlo Method (MCM) analysis focuses on the output derived from two distinct locations: the Lab and Home. Due to the differences in size between these locations, the distances between devices as input parameter vary, as illustrated in figures 4.3 and 4.4. In the following tables, only the last 5 iterations of the MCM output are presented, as space limitations in this research paper prevent the inclusion of all iterations, which can number in the thousands. For a comprehensive list of the data table, refer to the appendix. The full list of parameters used for the MCM analysis can be found in table 4.1.

Table 5.1: Monte Carlo Method output from lab.

| Device | $P_{tx}(dBm)$ | Penalty |
|---|---|---|
| 3, 5, 2, 5, 1, 5, 0, 0 | -20, 0, 0, -8, 0, -12, 0, -20 | 3000 |
| 3, 4, 1, 3, 0, 4, 1, 3 | -16, -8, -4, -20, 0, -12, -4, -20 | 3000 |
| 3, 4, 4, 1, 2, 4, 4, 2 | 4, -12, -20, -4, -8, -12, -20, -8 | 3000 |
| 2, 0, 1, 2, 0, 0, 1, 1 | -12, 4, -8, -8, -20, 0, -8, -20 | 4000 |
| 2, 5, 3, 3, 5, 2, 2, 4 | -8, 8, 0, -16, 0, -8, -20, 8 | 0 |

Table 5.2: Monte Carlo Method output from home.

| Device | $P_{tx}(dBm)$ | Penalty |
|---|---|---|
| 2, 0, 2, 2, 5, 5, 1, 1 | -12, -8, 8, -4, 0, 8, -20, -12 | 3000 |
| 4, 1, 1, 4, 0, 5, 1, 0 | -12, 4, 0, -8, 8, 8, -12, -20 | 4000 |
| 0, 2, 5, 2, 4, 2, 5, 4 | -20, -4, -12, -12, -4, -8, -20, -4 | 3000 |
| 1, 2, 0, 2, 1, 2, 0, 1 | -8, -8, -16, -16, -12, -8, -16, 4 | 4000 |

| | | |
|---|---|---|
| 2, 3, 5, 2, 2, 3, 4, 5 | 8, 8, -20, -8, -4, -16, 4, -16 | 0 |

The last row in each table indicates a penalty value of 0, which satisfies the mathematical constraints. When a constraint violation occurs, a penalty value of 1000 is added to the Penalty column. An optimal network configuration, which comprises different device types and initial transmission power, is represented by the absence of a penalty. Table 5.1 shows the MCM output from the lab location, where the final row demonstrates an optimal network configuration, with a penalty value of zero. Similarly, table 5.2 presents the MCM output from the home location, with the last row indicating an optimal configuration, also featuring a penalty value of 0.

Examining the rows with penalties in both tables, we can take the first row as an example. In this row, the penalty value is 3000, indicating three violations. According to the mathematical constraints, a leader router must be present in the network, represented by the number 4 in the device column. The absence of a leader router results in the first violation, adding 1000 to the penalty. The relevant mathematical constraints and models are detailed in equations 4.1, 4.2, 4.3, and 4.4.

The next constraint requires the number of routers and leaders to be equal to or greater than 3. However, the network configuration in the first row lacks a leader, leading to another violation. Lastly, a constraint mandates that the number of REEDs must be equal to the combined number of routers and leaders. The absence of a leader router in the network configuration causes the penalty value to reach 3000. The Monte Carlo Method continues iterating until it identifies an optimal network configuration without any constraint violations.

## 5.2 Genetic Algorithm Analysis

Similar to the Monte Carlo Method Analysis, the tables presented below display the output from the Genetic Algorithm for both lab and home locations, with the primary difference between the two scenarios being the distance between devices as input parameters. Unlike the MCM, GA directly provides the final result, showcasing the lowest feasible transmission power without any constraint violations. As GA emphasizes minimizing transmission power, storing all analyzed data from its output is unnecessary, except for the final result. The full list of parameters used in the GA analysis can be found in table 4.2.

Table 5.3: Genetic Algorithm output from lab.

| Device | $P_{tx}(dBm)$ | Total |
|---|---|---|
| 5, 5, 4, 3, 3, 2, 2, 2 | -20, -20, -20, -20, -20, -20, -20, -20 | -160 |

Table 5.4: Genetic Algorithm output from home.

| Device | $P_{tx}(dBm)$ | Total |
|---|---|---|
| 5, 5, 4, 3, 3, 2, 2, 2 | -20, -19, -20, -19, -18, -18, -16, -19 | -149 |

The Genetic Algorithm output for the lab location, as shown in table 5.3, achieved the lowest possible transmission power of -20 $dBm$ for all nodes in the network. This outcome is expected, given the network's short distances within the small lab setting. When devices are in close proximity to each other, there is no need to increase transmission power, as doing so would waste energy. In this scenario, GA successfully minimized transmission power for all nodes. Although it may appear that GA could have set the power even lower, it's important to note that -20 $dBm$ is the lowest limit, and going below that would depend on the mathematical constraints covering path loss and RSSI sensitivity.

Conversely, table 5.4 displays the GA output for the home location, where transmission power was not set to the lowest possible value for all nodes due to the larger area. The GA output produced a transmission power range from -16 to -20 $dBm$, which is still an impressive result compared to the maximum transmission power mode. This variation in transmission power reflects the differing distances between devices within the home network.

Lastly, the device columns display the same types of devices, which is due to the total number of devices being set to 8, as specified in the parameters table 4.1. According to the mathematical constraints, this represents the optimal network configuration derived from the MCM output. If the total number of devices in the network were to be increased, the network configuration would exhibit greater variation.

In addition to these results, examining the plots for both the lab and home locations provides further insight into the transmission power optimization process based on the number of generations. The X-axis of the plots represents the total number of populations, with 100 max populations being set for this research, as mentioned in the parameters table 4.2. The maximum number of populations is adjusted depending on the optimization process and requirements. The linear curve observed in the plots is influenced by the parameters used in the GA process, such as distances between devices and the selection method. As these factors change, the transmission process is affected, resulting in different curve patterns in the plots. This demonstrates the flexibility of the GA in adapting to various network configurations and optimization objectives.

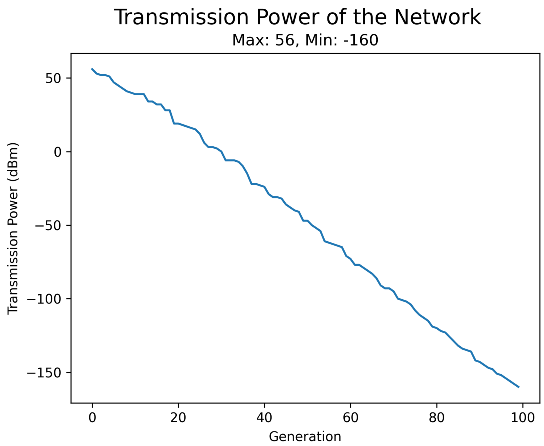


Figure 5.1: GA transmission power optimization for lab.

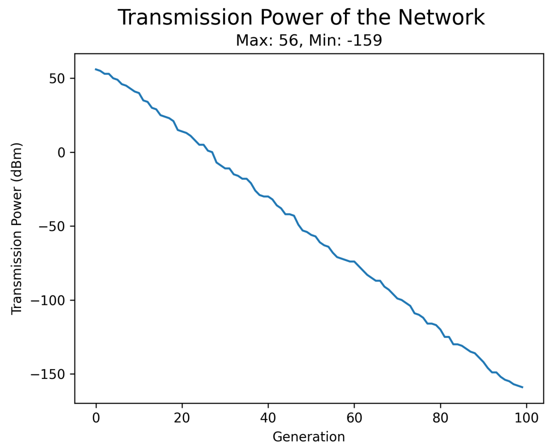


Figure 5.2: GA transmission power optimization for home.

## 5.3 Distance vs. Transmission Power Analysis

Understanding the relationship between distance and transmission power in the network is important for analyzing network configurations. By looking at the plots for both lab and home locations, this relationship becomes clearer. In these plots, the distance between devices is shown on the x-axis, while transmission power is displayed on the y-axis.

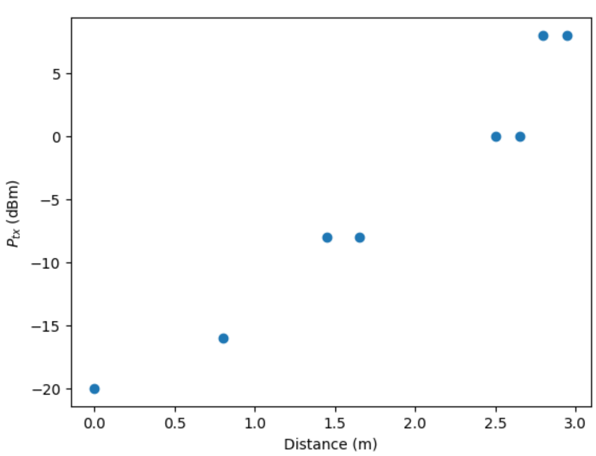


Figure 5.3: Transmission power vs. distance for lab location using MCM.

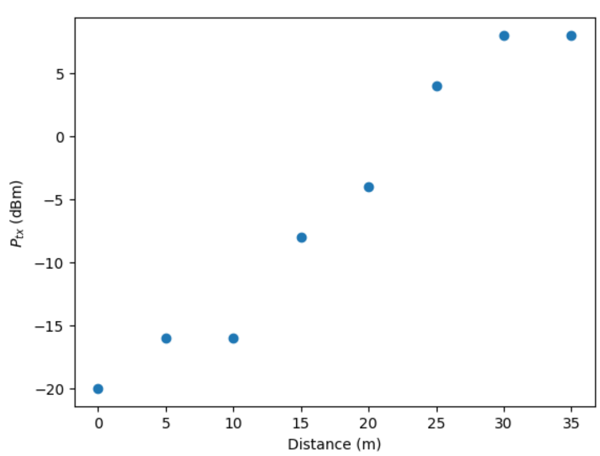


Figure 5.4: Transmission power vs. distance for home location using MCM.

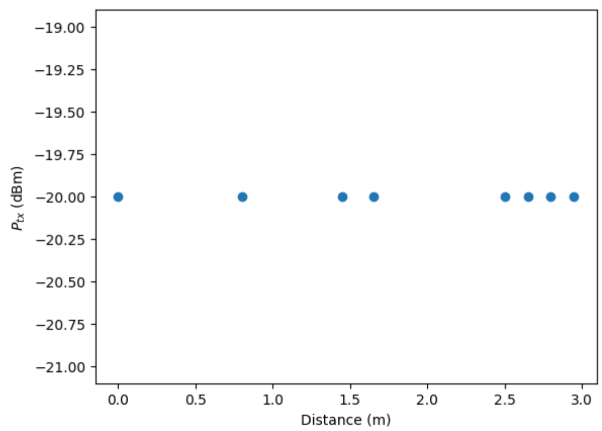


Figure 5.5: Transmission power vs. distance for lab location using GA.

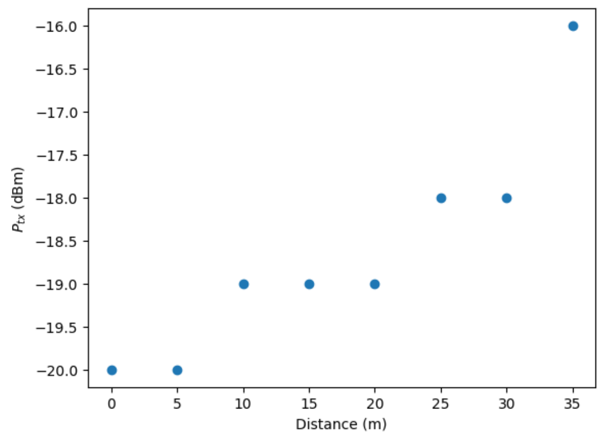


Figure 5.6: Transmission power vs. distance for home location using GA.

A closer look reveals that as the distance between devices increases, transmission power also increases. Conversely, devices closer to each other have lower transmission power settings. This pattern is expected because it is inefficient to use extra power for devices that are near each other. Instead, higher transmission power is needed to keep devices connected when they are farther apart.

Transmission power plays a key role in determining the coverage of Thread radio networks. Networks with higher transmission power settings can cover larger areas, ensuring that devices stay connected even when they are separated by greater distances [4]. Effective power management is important for optimizing network performance and saving energy.

## 5.4 Path Loss Analysis

The relationship between path loss, distance, and environment is a critical aspect of wireless communication. Two plots are provided to illustrate the path loss between devices at both lab and home locations. As anticipated, these plots demonstrate that the greater the distance between devices, the higher the path loss. It is important to note that even at close distances, higher path loss can occur due to environmental factors, as shown in table 2.1's path loss exponent.

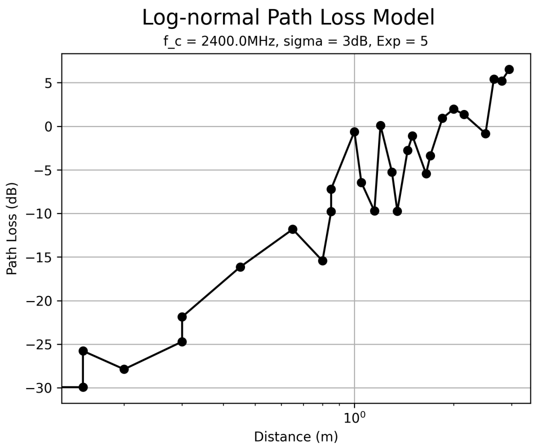


Figure 5.7: Path loss for lab location.

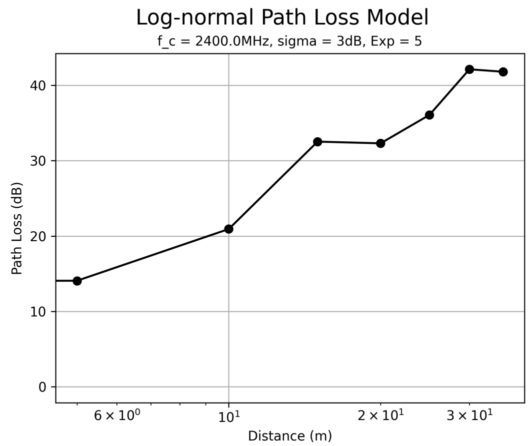


Figure 5.8: Path loss for hoome location.

Free space environments, such as satellite communication, typically exhibit lower path loss, while indoor locations like homes tend to experience higher path loss due to the presence of obstacles, such as walls and furniture [10]. The plots confirm the expected relationship between path loss, distance, and environment.

The first plot, representing the lab location, displays lower path loss between devices. This can be attributed to the controlled environment and shorter distances between devices. In contrast, the second plot, showcasing the home location, reveals higher path loss between devices. This increase in path loss can be attributed to both the larger distances between devices and the presence of obstacles in the home environment, which impede wireless communication signals.

## 5.5 Algorithmic Parameter Analysis

So far, the analyses for MCM and GA have been based on the applied values to the experimental prototype, with the only differing parameter being the distance between the two different locations, lab and home. The previous experiments provided valuable insights into the performance of both algorithms within the tested parameters. However, it is also important to explore their behavior with different parameters and larger distances for a more comprehensive understanding. To achieve this, a parameter table has been created using the following imaginary values:

Table 5.5: Algorithmic parameter analysis.

| Parameter | Value |
|---|---|
| $d$ | 10 $m$ |
| $D_0$ | 0.35 $m$ |
| $n$ | 6.0 |

| | |
|---|---|
| $\sigma$ | 5.0 $dB$ |
| Population size | 30 |
| Max iteration | 20 |
| Mutation rate | 0.3 |
| Selection method | Tournament |
| Mutation method | Random |

These parameters are described in tables 4.1 and 4.2. Although increasing the distance would impact the number of devices and the computational power required for the MCM, the chosen distance represents a reasonable compromise for the given number of devices. In response to the sub-research question 5, the tables below present the MCM and GA outputs based on these different parameters, demonstrating how the algorithms behave under different conditions and larger distances:

Table 5.6: Monte Carlo Method output based on different parameters.

| Device | $P_{tx}(dBm)$ | Penalty |
|---|---|---|
| 3, 4, 5, 5, 3, 2, 2, 2 | -12, -12, 8, 4, -4, -16, -4, 8 | 0 |

Table 5.7: Genetic Algorithm output based on different parameters.

| Device | $P_{tx}(dBm)$ | Total |
|---|---|---|
| 5, 5, 4, 3, 3, 2, 2, 2 | -11, -12, -9, 8, 6, -4, 5, 7 | -10 |

While the MCM table may not show any significant differences compared to previous analyses, the transmission power from the GA table does present interesting observations. Upon closer inspection, the transmission power is no longer at the edge range, as seen in past analyses. This outcome is expected since the current transmission power is calculated from much larger distances, while the past analyses were based on closer distances. In smaller distances, lower transmission power values are sufficient to maintain a reliable connection between devices, as the signal propagation is stronger. On the other hand, larger distances require higher transmission power values to ensure the signal can effectively reach and maintain a stable connection with other devices in the network.

In the context of the GA plot for transmission power optimization, the optimization line is no longer linear, likely due to the different parameters used, especially the selection method. The max value reaches a high of 5901 $dBm$ but drops to -17 $dBm$ at the lowest point, a notable result. The Y-axis, which shows the transmission power made up of both penalties for each constraint violation and the output transmission power for each iteration from GA, is understandably higher. Even though the plot reached -17 $dBm$, the best transmission power is the one with no penalty, as shown by the GA output in the table.

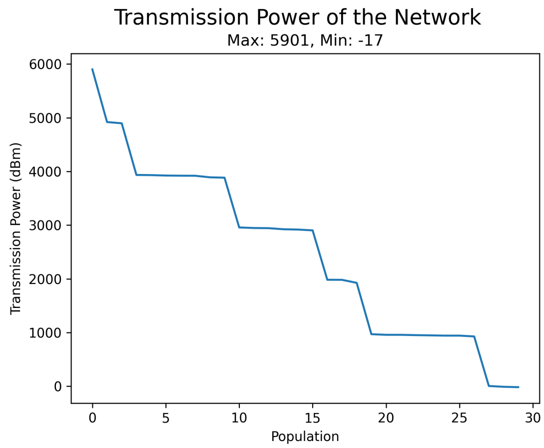


Figure 5.9: GA transmission power optimization based on different parameters.

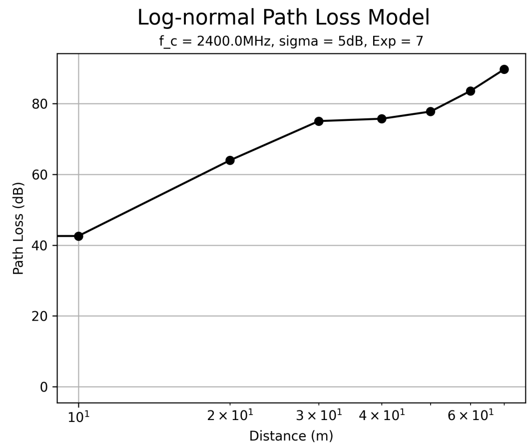


Figure 5.10: Path loss based on different parameters for large distance.

In addition to the impact on transmission power, the different parameters also affect path loss. The path loss plot, based on these different network parameters, shows a much higher path loss value as expected. This higher path loss is in line with the trend observed in past analyses, where path loss increased with higher distances. While distance is the primary contributor to these changes, other factors, such as the variance of components $\sigma$, reference distance $d$, and the signal power decay with distance in the path loss model $n$, also play a role. The path loss figure 5.10 demonstrates these differences, providing valuable insights into how the various parameters influence path loss in different scenarios.

## 5.6 Experimental Data Analysis

The following analysis delves into a comprehensive data table that compares two distinct modes of operation in communication systems. The primary focus of this data table is to evaluate the current consumption of each mode, with the ultimate goal of identifying the more efficient method for power conservation. To accomplish this, an array of different parameters are considered. The subsequent sections provide an in-depth examination and interpretation of the data, aiming to answer the research questions and offer valuable insights into power optimization strategies.

Table 5.8: Experimental data analysis across different scenarios.

| Method | Loc | Type | Mode | Ping | $T$ $(s)$ | $P_{tx}$ $(dBm)$ | Node | Current consumption $(mA)$ $I_1$ Mean | $I_1$ Max | $I_1$ Min | $I_2$ Mean | $I_2$ Max | $I_2$ Min |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Maximum | Lab | No Sensor | N/A | 0 | 60 | 8 | BR1 | 6.22 | 18.16 | 1.5 | 6.2 | 16.86 | 1.01 |
| | | | | | | | BR2 | 6.43 | 18.83 | 1.48 | 6.43 | 17.77 | 1.12 |
| | | | | | | | R1 | 9.72 | 18.83 | 7.3 | 9.78 | 21.22 | 7.44 |
| | | | | | | | R2 | 9.73 | 19.11 | 7.12 | 9.73 | 20.53 | 7.35 |
| | | | | | | | R3 | 9.65 | 18.12 | 7.16 | 9.78 | 20.14 | 7.53 |
| | | | | | | | ED1 | 11.88 | 21.49 | 6.05 | 11.79 | 20.92 | 5.99 |
| | | | | | | | ED2 | 11.87 | 21.39 | 6.14 | 11.69 | 21.07 | 6.13 |
| | | | | | | | ED3 | 11.6 | 21.58 | 5.87 | 11.65 | 21.26 | 5.95 |
| | | Ping | | 50 | | | BR1 | 6.29 | 17.96 | 1.51 | 6.27 | 18.16 | 1.28 |
| | | | | | | | BR2 | 6.64 | 20.73 | 1.4 | 6.48 | 19.07 | 1.47 |
| | | | | | | | R1 | 9.91 | 20.0 | 2.08 | 9.83 | 21.56 | 6.9 |
| | | | | | | | R2 | 9.82 | 19.27 | 6.62 | 9.75 | 20.87 | 6.76 |
| | | | | | | | R3 | 9.89 | 19.95 | 6.9 | 9.82 | 20.68 | 6.8 |
| | | | | | | | ED1 | 11.86 | 21.66 | 6.08 | 11.83 | 22.35 | 6.08 |
| | | | | | | | ED2 | 11.98 | 22.3 | 6.13 | 11.17 | 21.36 | 6.13 |
| | | | | | | | ED3 | 11.89 | 21.9 | 6.04 | 11.66 | 21.8 | 5.95 |
| | Home | No Sensor | | 0 | 300 | | BR1 | 6.62 | 18.2 | 1.01 | 6.2 | 17.05 | 1.07 |
| | | | | | | | BR2 | 6.41 | 18.35 | 1.05 | 6.42 | 17.96 | 1.04 |
| | | | | | | | R1 | 9.7 | 19.56 | 2.04 | 9.76 | 21.51 | 4.61 |
| | | | | | | | R2 | 9.65 | 19.12 | 2.28 | 9.72 | 20.82 | 4.56 |
| | | | | | | | R3 | 9.7 | 19.32 | 4.61 | 9.78 | 20.24 | 2.05 |
| | | | | | | | ED1 | 11.73 | 21.26 | 5.99 | 11.76 | 21.17 | 6.04 |
| | | | | | | | ED2 | 11.63 | 21.12 | 5.9 | 11.68 | 20.87 | 5.99 |
| | | | | | | | ED3 | 11.73 | 21.46 | 5.81 | 11.64 | 21.61 | 5.81 |
| | | Ping | | 290 | | | BR1 | 6.41 | 19.56 | 0.3 | 6.28 | 18.4 | 1.09 |
| | | | | | | | BR2 | 6.62 | 20.39 | 1.08 | 6.49 | 19.32 | 1.05 |
| | | | | | | | R1 | 9.92 | 20.14 | 4.56 | 9.85 | 21.66 | 2.33 |
| | | | | | | | R2 | 9.83 | 19.61 | 4.65 | 9.76 | 21.07 | 4.65 |
| | | | | | | | R3 | 9.89 | 19.85 | 2.14 | 9.84 | 21.87 | 2.04 |
| | | | | | | | ED1 | 11.9 | 21.85 | 5.99 | 11.84 | 22.64 | 5.99 |
| | | | | | | | ED2 | 11.77 | 21.61 | 5.99 | 11.75 | 21.46 | 5.99 |
| | | | | | | | ED3 | 11.84 | 22.15 | 5.99 | 11.67 | 22.0 | 5.86 |
| Optimized | Lab | No Sensor | MCM | 0 | 60 | -8 | BR1 | 6.22 | 16.67 | 1.34 | 6.19 | 16.76 | 1.68 |
| | | | | | | 8 | BR2 | 6.45 | 18.93 | 1.66 | 6.41 | 18.35 | 1.78 |
| | | | | | | -16 | R1 | 9.82 | 12.88 | 7.44 | 9.76 | 12.74 | 7.03 |
| | | | | | | 0 | R2 | 9.71 | 12.83 | 7.39 | 9.7 | 12.83 | 7.35 |
| | | | | | | 0 | R3 | 9.8 | 12.83 | 7.39 | 9.8 | 20.09 | 7.48 |
| | | | | | | -8 | ED1 | 11.86 | 15.1 | 6.17 | 11.76 | 15.1 | 6.08 |
| | | | | | | -20 | ED2 | 11.76 | 14.91 | 6.13 | 11.69 | 14.95 | 6.08 |
| | | | | | | 8 | ED3 | 11.78 | 21.17 | 6.13 | 11.64 | 21.66 | 5.99 |
| | | | GA | | | -20 | BR1 | 6.2 | 16.79 | 1.57 | 6.2 | 16.82 | 1.43 |
| | | | | | | | BR2 | 6.42 | 15.88 | 1.6 | 6.41 | 17.17 | 1.57 |
| | | | | | | | R1 | 9.77 | 12.88 | 7.3 | 9.76 | 12.83 | 7.39 |
| | | | | | | | R2 | 9.68 | 12.83 | 7.12 | 9.73 | 12.83 | 7.44 |
| | | | | | | | R3 | 9.76 | 12.6 | 7.12 | 9.78 | 12.79 | 7.21 |
| | | | | | | | ED1 | 11.84 | 15.1 | 6.13 | 11.76 | 15.24 | 5.9 |
| | | | | | | | ED2 | 11.7 | 14.81 | 6.08 | 11.64 | 15.0 | 6.04 |
| | | | | | | | ED3 | 11.73 | 15.0 | 6.04 | 11.7 | 15.05 | 6.04 |
| | | Ping | MCM | 50 | | -8 | BR1 | 6.24 | 17.32 | 0.94 | 6.22 | 17.32 | 1.31 |
| | | | | | | 8 | BR2 | 6.6 | 20.09 | 1.28 | 6.48 | 19.17 | 1.38 |
| | | | | | | -16 | R1 | 9.78 | 13.4 | 4.78 | 9.8 | 13.07 | 6.9 |
| | | | | | | 0 | R2 | 9.76 | 13.02 | 2.83 | 9.69 | 13.07 | 6.9 |
| | | | | | | 0 | R3 | 9.82 | 17.19 | 2.95 | 9.85 | 20.68 | 6.9 |
| | | | | | | -8 | ED1 | 11.82 | 15.38 | 6.13 | 11.8 | 15.28 | 6.04 |
| | | | | | | -20 | ED2 | 11.65 | 15.28 | 5.99 | 11.6 | 15.0 | 6.04 |
| | | | | | | 8 | ED3 | 11.88 | 21.76 | 6.04 | 11.66 | 21.76 | 5.99 |
| | | | GA | | | -20 | BR1 | 6.22 | 17.02 | 1.0 | 6.21 | 16.9 | 1.01 |
| | | | | | | | BR2 | 6.43 | 17.18 | 1.28 | 6.42 | 16.92 | 1.05 |
| | | | | | | | R1 | 9.76 | 13.3 | 4.78 | 9.79 | 13.21 | 7.03 |
| | | | | | | | R2 | 9.71 | 13.02 | 4.69 | 9.69 | 13.07 | 6.85 |
| | | | | | | | R3 | 9.79 | 13.21 | 5.01 | 9.77 | 13.02 | 6.9 |
| | | | | | | | ED1 | 11.81 | 15.28 | 6.04 | 11.77 | 15.28 | 5.99 |
| | | | | | | | ED2 | 11.7 | 15.19 | 6.13 | 11.6 | 15.0 | 5.99 |
| | | | | | | | ED3 | 11.72 | 15.24 | 5.99 | 11.68 | 15.24 | 5.99 |
| | Home | No Sensor | MCM | 0 | 300 | 8 | BR1 | 6.22 | 17.58 | 1.04 | 6.2 | 17.29 | 0.98 |
| | | | | | | 8 | BR2 | 6.42 | 18.16 | 1.06 | 6.41 | 18.4 | 1.12 |
| | | | | | | -8 | R1 | 9.75 | 13.07 | 2.04 | 9.75 | 12.88 | 4.74 |
| | | | | | | -20 | R2 | 9.73 | 12.93 | 4.74 | 9.71 | 12.83 | 4.69 |
| | | | | | | -4 | R3 | 9.75 | 12.83 | 4.65 | 9.79 | 16.3 | 2.95 |
| | | | | | | -16 | ED1 | 11.75 | 15.1 | 5.95 | 11.75 | 15.1 | 5.99 |
| | | | | | | 4 | ED2 | 9.73 | 12.93 | 4.74 | 9.71 | 12.83 | 4.69 |
| | | | | | | -16 | ED3 | 9.75 | 12.83 | 4.65 | 9.79 | 16.3 | 2.95 |
| | | | GA | | | -20 | BR1 | 6.19 | 16.82 | 1.02 | 6.2 | 17.02 | 1.02 |
| | | | | | | -19 | BR2 | 6.41 | 16.92 | 0.91 | 6.41 | 17.05 | 0.97 |
| | | | | | | -19 | R1 | 9.76 | 12.83 | 1.99 | 9.75 | 12.93 | 4.78 |
| | | | | | | -20 | R2 | 9.72 | 12.74 | 2.34 | 9.7 | 12.93 | 2.26 |
| | | | | | | -18 | R3 | 9.75 | 12.88 | 4.74 | 9.78 | 12.88 | 4.69 |
| | | | | | | -18 | ED1 | 11.75 | 15.1 | 5.9 | 11.76 | 15.1 | 5.99 |
| | | | | | | -16 | ED2 | 11.67 | 14.95 | 5.99 | 11.63 | 15.24 | 5.99 |
| | | | | | | -19 | ED3 | 11.73 | 15.1 | 6.08 | 11.68 | 18.98 | 0.25 |
| | | Ping | MCM | 290 | | 8 | BR1 | 6.42 | 19.17 | 0.33 | 6.28 | 18.25 | 1.04 |
| | | | | | | 8 | BR2 | 6.63 | 19.51 | 1.05 | 6.49 | 19.32 | 1.13 |
| | | | | | | -8 | R1 | 9.73 | 16.45 | 2.04 | 9.8 | 13.21 | 2.29 |
| | | | | | | -20 | R2 | 9.67 | 13.21 | 2.02 | 9.69 | 13.02 | 4.65 |
| | | | | | | -4 | R3 | 9.73 | 16.17 | 2.12 | 9.8 | 13.21 | 4.74 |
| | | | | | | -16 | ED1 | 11.72 | 15.48 | 5.95 | 11.72 | 15.33 | 5.95 |
| | | | | | | 4 | ED2 | 11.69 | 18.11 | 5.9 | 11.65 | 18.25 | 5.95 |
| | | | | | | -16 | ED3 | 11.65 | 15.28 | 5.95 | 11.67 | 15.24 | 5.86 |
| | | | GA | | | -20 | BR1 | 6.2 | 17.31 | 1.03 | 6.21 | 16.99 | 1.05 |
| | | | | | | -19 | BR2 | 6.4 | 17.34 | 1.08 | 6.43 | 16.98 | 0.94 |
| | | | | | | -19 | R1 | 9.73 | 13.76 | 2.01 | 9.79 | 13.3 | 2.28 |
| | | | | | | -20 | R2 | 9.68 | 14.25 | 2.03 | 9.69 | 15.24 | 2.21 |
| | | | | | | -18 | R3 | 9.76 | 13.21 | 4.56 | 9.78 | 13.12 | 4.65 |
| | | | | | | -18 | ED1 | 11.74 | 15.28 | 5.99 | 11.78 | 15.33 | 6.08 |
| | | | | | | -16 | ED2 | 11.64 | 15.24 | 5.99 | 11.62 | 15.19 | 5.95 |
| | | | | | | -19 | ED3 | 11.69 | 15.52 | 5.9 | 11.66 | 15.28 | 5.9 |

In the analysis of the table 5.6, a detailed comparison between the maximum and optimized modes can be made, taking into account various parameters, including the mean, max, and min current values, location, iteration, and device type. Here is a more comprehensive overview of the data:

### 5.6.1 Mean, Max, and Min Current Analysis

The analysis of the mean, max, and min current ($mA$) across all devices, locations, and methods revealed various trends. Overall, the mean current values ranged from 6.19 $mA$ to 11.98 $mA$, with the lowest values observed in the BR series devices and the highest values in the ED series devices. The maximum current values varied from 12.6 $mA$ to 22.64 $mA$, while the minimum current values were between 0.25 $mA$ and 7.53 $mA$. This broad range of values suggests that different devices, methods, and environments may have significant impacts on the current consumption of the devices tested.

### 5.6.2 Location-Specific Analysis

The location-specific analysis demonstrated that the devices' performance differed depending on whether they were tested in a lab or at home. In general, the mean, max, and min current values were higher in the lab setting compared to the home setting. This could be attributed to the controlled environment in the lab, which may have led to more stable and consistent performance across devices. This finding answer sub-research question 9, which aims to investigate the impact of location on power optimization performance.

### 5.6.3 Iteration-Specific Analysis

In comparing the first and second iterations, it was observed that the mean, max, and min current values showed little variation. This indicates that the performance of the devices was consistent across both iterations. However, some minor differences were noticed, such as a slight increase or decrease in the current values for some devices between iterations. This could be due to the variations in the environment or the devices' behavior during the testing period. This analysis answers sub-research question 6, which aims to explore the differences in power optimization performance between different iterations for both maximum and optimized modes.

### 5.6.4 Device-Specific Analysis

The device-specific analysis revealed that the BR series devices consistently exhibited the lowest mean, max, and min current values compared to the R and ED series devices. In contrast, the ED series devices had the highest mean, max, and min current values. This suggests that the BR series devices may be more energy-efficient than the other devices, while the ED series devices may require more power to operate. This finding answer sub-research question 7, which aims to compare the power optimization performance of different devices in Maximum and Optimized modes.

### 5.6.5 Type-Specific Analysis

When comparing devices with no sensor versus devices with a ping, it was found that devices without a sensor tended to have slightly lower mean, max, and min current values. This indicates that the presence of a sensor may increase power consumption in certain devices.

Further investigation into this finding revealed that devices with sensors require additional power to operate the sensor and transmit sensor data, leading to increased power consumption. In contrast, devices without sensors do not have these additional power requirements, resulting in lower power consumption overall.

### 5.6.6 Mode-Specific Analysis

The mode-specific analysis revealed that the devices' performance was affected by the MCM and GA modes. In general, the mean, max, and min current values were higher in the MCM mode compared to the GA mode. This suggests that the MCM mode require more power to operate and maintain, while the GA mode may offer more energy-efficient performance.

Furthermore, when comparing the power optimization performance of the MCM and GA modes, it was found that the GA mode outperformed the MCM mode in terms of energy efficiency. Devices operating in the GA mode consumed less power while still achieving comparable levels of performance, indicating that this mode may be a better option for power optimization. This finding supports the sub-research question 10 on the effect of mode on power optimization, indicating that the choice of mode can have a significant impact on power consumption and optimization performance.

### 5.6.7 Method-Specific Analysis

Lastly, the method-specific analysis showed that the mean, max, and min current values were lower in the optimized method compared to the maximum method. This indicates that the optimized method may provide a more energy-efficient solution for the devices tested, as it consumes less power overall. This insight could prove useful when selecting a method for future deployments to reduce energy consumption and improve device performance. This finding answer sub-research question 8, which aims to explore the correlation between mean, max, and min current values and the efficiency of power optimization for different methods.

In conclusion, the data analysis of the mean, max, and min current values across various parameters, including iteration, device type, location, sensor presence, mode, and method, revealed distinct trends in the devices' power consumption. The BR series devices consistently showed the lowest current values, suggesting better energy efficiency compared to other device types. Devices tested in the lab displayed higher current values than those in the home setting, indicating the influence of environmental factors on device power consumption.

Furthermore, devices without sensors generally consumed less power, and the GA mode demonstrated lower current values compared to the MCM mode. Finally, the optimized method appeared to be a more energy-efficient solution compared to the maximum method.

## 5.7 Experimental Results

In this section, the power efficiency of the devices under study is examined, focusing on the maximum and optimized methods applied to MCM and GA modes. The analysis considers the error values obtained from the first and second iteration MCM and GA values, providing insights into the variability and precision of the measurements. This results-driven perspective allows for a comprehensive understanding of the performance differences between the methods and modes under investigation.

Table 5.9: Experimental results across different scenarios with errors.

| Method | Location | Type | Iteration (%) | | | | Error (%) | |
|---|---|---|---|---|---|---|---|---|
| | | | $I_1$ | | $I_2$ | | | |
| | | | Mode | | | | | |
| | | | MCM | GA | MCM | GA | MCM | GA |
| Optimized | Lab | No Sensor | 25.69 | 26.42 | 20.6 | 26.31 | 5.09 | 0.11 |
| | | Ping | 18.52 | 27.07 | 18.39 | 28.47 | 0.13 | 1.4 |
| | Home | No Sensor | 27.12 | 25.92 | 24.38 | 24.25 | 2.74 | 1.67 |
| | | Ping | 19.24 | 26.19 | 24.84 | 27.47 | 5.6 | 1.28 |

The table 5.9 presents a comprehensive comparison of MCM and GA modes in the Optimized method, with a focus on the percentage values calculated from the maximum current values obtained in previous analyses. Considering the maximum current values for the power optimization process is important because it helps identify the devices' peak current usage. This method offers a clearer understanding of the devices' power efficiency in different modes and iterations. By focusing on the highest current values, a more accurate assessment of the effectiveness of the power optimization process can be achieved, especially during the most demanding situations. This approach addresses the sub-research question 11, which aims to understand the impact of power optimization methods on devices' power efficiency across different modes and iterations.

In the optimized method, the lab location exhibits a higher percentage for no sensor and ping types in both MCM and GA modes when compared to the home location. Specifically, for the no sensor type, the lab location has a 25.69% and 26.42% improvement in MCM and GA modes, respectively, in the first iteration, while for the ping type, the lab location has an 18.52% and 27.07% improvement in MCM and GA modes, respectively. In the second iteration, the lab location maintains its higher performance with 20.6% and 26.31% improvements in MCM and GA modes for the no sensor type, and 18.39% and 28.47% improvements in MCM and GA modes for the ping type. This observation indicates that the devices in the lab location demonstrate better power efficiency.

On the other hand, in the home location, the no sensor type shows a 27.12% and 25.92% improvement in MCM and GA modes, respectively, in the first iteration, while for the ping type, there is a 19.24% and 26.19% improvement in MCM and GA modes, respectively. In the second iteration, the home location has a 24.38% and 24.25% improvement in MCM and GA modes for the no sensor type, and 24.84% and 27.47% improvements in MCM and GA modes for the ping type.

Errors were calculated based on the differences between the first and second iteration values for MCM and GA modes. The presence of errors might be attributed to various factors, such as device inconsistencies, environmental factors, or potential limitations in the experimental setup. These errors affect the research by introducing a level of uncertainty in the results, making it necessary to interpret the findings with caution, which addresses the second sub-research question 12. For instance, in the lab location, the no sensor type has errors of 5.09% and 0.11% in MCM and GA modes, while in the home location, errors are 2.74% and 1.67% for the same modes.

In conclusion, the analysis demonstrates the effectiveness of parameter optimization in developing a power-optimized Thread mesh wireless network, addressing the main research question and the problem definition. Both MCM and GA modes outperform the maximum method, with GA optimization consistently offering better optimization results than MCM across different locations and device types. This indicates that the GA approach significantly contributes to lowering power consumption in Thread mesh wireless networks by optimizing transmission power parameter more effectively than the MCM method.

The algorithmic approach, specifically the GA optimization, can be integrated into the system by adjusting transmission power parameter according to the optimization results. By monitoring the network conditions and transmission power, the Thread mesh wireless network can maintain optimal energy efficiency. The results provide a solid foundation for future exploration and enhancements in power optimization using algorithmic approaches, addressing the challenges of consuming higher power, ultimately realizing the full potential of Thread-based wireless communication in a wide range of low-powered IoT network fields.

# Chapter 6

# Conclusions and Recommendations

## 6.1 Conclusions

This research on power optimization in Thread mesh wireless networks using transmission power as a parameter has demonstrated the effectiveness of algorithmic approaches, particularly Genetic Algorithm, in reducing power consumption. Genetic Algorithm optimization consistently outperformed both Monte Carlo Method mode and maximum method across different locations and device types, with improvements of up to 28.47% in power efficiency and error rates as low as 0.11%. Monte Carlo Method also achieved improvements of up to 27.12% in power efficiency, while errors reached up to 5.6%. These results not only enhance the performance of MOOD-Sense initiatives and other IoT applications but also contribute to sustainable and energy-efficient IoT network implementation. By adhering to responsible research and innovation principles, this study ensures the development of an optimized system design adaptable for various applications beyond MOOD-Sense, promoting energy-conserving, environmentally friendly, and sustainable IoT devices and network integration. This research demonstrates that optimizing transmission power using algorithmic approaches, specifically Genetic Algorithm optimization, can significantly reduce power consumption in Thread mesh wireless networks, paving the way for future exploration and enhancements in power optimization using algorithmic approaches, addressing the challenges of consuming higher power, and ultimately realizing the full potential of Thread-based wireless communication in a wide range of low-powered fields.

## 6.2 Recommendations

Considering the conclusions from this research, several recommendations for future work are proposed to further enhance power optimization in Thread mesh wireless networks. These suggestions aim to build on the foundation laid by this research and contribute to the ongoing development of Thread mesh wireless networking technologies.

1. **Dynamic Transmission Power Allocation**: Develop a custom SDK on top of

existing platforms like Zephyr, nRF, or OpenThread that automatically sets the transmission power based on the distances between devices without requiring manual action and reflashing the device. By automating this process, the network can achieve better energy efficiency, adapt to changes in device locations more effectively, and minimize the need for human intervention to update transmission power settings, making the Thread network more sustainable and user-friendly.

2. **Exploring Different Thread Devices**: Investigate the impact of different Thread devices, such as Full Thread Devices (FTD), Minimal Thread Devices (MTD), and Sleepy Thread Devices (STD), on power consumption. By understanding the unique characteristics and energy requirements of each device type, the most suitable Thread devices can be selected to improve overall network efficiency. A thorough evaluation of device capabilities, power requirements, and application-specific needs can help guide the selection process for an optimized network configuration.

3. **Investigating Low-Power SoC Options**: Assess various low-power System-on-Chip (SoC) options available on the market to determine the most energy-efficient solutions for the Thread network. By considering different devices with better low-powered SoC capabilities, the overall energy consumption of the network can be reduced, leading to a more sustainable and efficient network. This exploration can help identify devices that meet the performance requirements of the network while minimizing power consumption and maximizing energy efficiency.

Implementing these recommendations can help future research advance the optimization of Thread mesh wireless networks, ultimately leading to more efficient IoT wireless networking solutions.

# Definitions and Abbreviations

Here is a list of abbreviations used throughout the research, along with their short definitions:

1. **IoT** - Internet of Things: A network of interconnected devices and sensors that communicate and share data over the internet.

2. **MCU** - Microcontroller Unit: A small, integrated computer on a single chip, used for embedded systems and control applications.

3. **UWB** - Ultra-Wideband: A radio technology that uses a wide frequency range for high data rate, short-range communication.

4. **MCM** - Monte Carlo Method: A computational method that uses random sampling to solve complex problems and estimate results.

5. **GA** - Genetic Algorithm: A search heuristic inspired by natural selection and genetics, used to optimize complex problems.

6. **mA** - milliampere: A unit of electric current equal to one-thousandth of an ampere.

7. **uA** - microampere: A unit of electric current equal to one-millionth of an ampere.

8. **dBm** - decibel-milliwatts: A unit of power level used to express the ratio of power in decibels relative to 1 milliwatt.

9. **WSN** - Wireless Sensor Network: A network of small, low-power devices that communicate wirelessly.

10. **RF** - Radio Frequency: Electromagnetic wave frequencies used for wireless communication.

11. **dB** - decibel: A unit of measurement used to express the ratio of two values in a logarithmic scale.

12. **FTD** - Full Thread Device: A node in a Thread network capable of routing traffic and participating in network management functions.

13. **MTD** - Minimal Thread Device: A node in a Thread network with limited routing capabilities, primarily functioning as an end device for low-power operation.

14. **STD** - Sleepy Thread Device: A low-power node in a Thread network that periodically wakes up to communicate before returning to sleep mode.

15. **SoC** - System on a Chip: An integrated circuit that combines multiple electronic components, such as a microprocessor, memory, and interfaces, on a single chip.

16. **nRF** - Nordic Semiconductor's RF series: A family of wireless SoCs developed by Nordic Semiconductor, designed for ultra-low power consumption and high-performance wireless connectivity.

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# Appendix

This Appendix provides various resources and links related to the research project. These resources include the full dataset analysis, algorithms, custom implementations, and output datasets. Due to these materials' large size and complexity, it is not feasible to include them directly in the research paper. Instead, the links in the following sections grant access to the complete datasets, algorithms, and implementations, allowing interested readers to explore the project in greater detail and better understand the methodology, optimization techniques, and findings. The sections below outline the resources available in the Appendix.

## 1 Dataset Analysis

This section provides the link to the Dataset Analysis Repository on GitLab. This repository contains a comprehensive set of analyses performed for the project. Due to the extensive nature of the analyses, including them all in this paper is not feasible. By sharing the repository, readers can access detailed studies and better understand the project's intricacies. The repository can be accessed using the following link: `https://gitlab.com/mmikhan/threadpowerprofiler/`

## 2 Dataset

The complete dataset, too large to include within the research paper, is available on GitLab. This dataset contains detailed information on the performance of the Thread network under various conditions and configurations. The original dataset is in binary format but has been converted to CSV for convenience and easier access. Access the dataset here: `https://gitlab.com/mmikhan/threadpowerprofiler/`

## 3 Algorithm

This section links the complete algorithm consisting of the Monte Carlo Method and Genetic Algorithm implementations on GitHub. This repository houses the code and documentation required to understand and replicate the optimization techniques used in this research project. Access the algorithm here: `https://github.com/mmikhan/ThreadNetPowerOptGA`

# 4 nRF Thread Client and Server Custom Implementation

This part presents the custom implementation of the nRF Thread Client and Server used in the physical prototype. This implementation was essential to successfully deploying and testing the optimized Thread network. Access the nRF Thread Client and Server custom implementation here: `https://github.com/mmikhan/Connecta`

# 5 Optimization Results

Finally, this section provides access to the large output dataset from Monte Carlo Method and Genetic Algorithm simulations. This dataset is crucial for understanding the outcomes of the optimization techniques and their impact on the energy efficiency and performance of the Thread network. Access the output dataset here: `https://gitlab.com/mmikhan/threadpowerprofiler/`

The resources presented in the Appendix thoroughly examine the research project, its methodology, and the optimization techniques utilized. Through carefully studying these materials, a comprehensive understanding of the project's development, implementation, and outcomes can be obtained, thereby enriching the overall context of the research.